NBER WORKING PAPER SERIES

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Working Paper 25432
http://www.nber.org/papers/w25432

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2019

We thank Chuck Eesley, Tom Fingar, Hongbin Li, Lianfa Luo, Gérard Roland, participants at 2018 AIEA-NBER Conference and seminar participants at CIDEG (Center for Industrial Development and Environmental Governance) (Tsinghua University) for helpful comments. We also thank the participating firms and employees who welcomed CEES enumerators to their firms and completed the survey in 2015 and 2016.We have received financial supports from the Key Project of Philosophy and Social Sciences Research from the Ministry of Education of China (Approval No. 15JZD023), the National Key Technology Research and Development Program of the Ministry of Science and Technology of China (Approval No. 2015BAH27F01), the National Key Research and Development Program of China (Approval No. 2016YFC0801906) and the Key Project of National Social Science Fund (Approval No. 16ZDA045). All remaining errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Do Innovation Subsidies Make Chinese Firms More Innovative? Evidence from the China Employer Employee Survey
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NBER Working Paper No. 25432
January 2019, Revised February 2019
JEL No. O25,O38,P48

ABSTRACT

The Chinese government has been using various subsidies to encourage innovations by Chinese firms. This paper examines the allocation and impacts of innovation subsidies, using the data from the China Employer Employee Survey (CEES). We find that the innovation subsidies are preferentially allocated to state owned firms and politically connected firms. Of these two (state ownership and political connection), political connection is more important in determining the allocation. We also find that the firms that receive innovation subsidies file and receive more patents, are more likely to introduce new products, but do not necessarily file and receive more patents abroad. Finally, the firms that receive innovation subsidies do not have higher productivity, more profits, or larger market shares. Overall, the results point to inefficiency of allocation of innovation subsidies and show that the subsidies encourage only incremental innovations and not radical ones.

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1. Introduction

Motivated by the realization that China's economic growth model that relied on cheap labor, capital deepening supported by high savings (depressed consumption), and technology mostly coming from advanced foreign countries is about to end, the Chinese government has been trying to encourage innovations by Chinese firms through various subsidy programs. This paper studies allocation and impacts of the innovation subsidies in China. We examine what type of firms are more likely to receive the innovation subsidies and if the subsidized firms are more likely to be innovative (measured by the number of patents and the likelihood of introducing new products), productive, and profitable.

In addition to improve our understanding on China's innovation policy, our paper contributes to three areas of economic inquiry. First, the paper builds on the literature on the rationales of the public support of research and development (R&D) investment. It is recognized that innovation is an important driving force of the long-run economy growth (Abramovitz, 1956; Solow, 1957; Romer, 1990; Aghion and Howitt, 1992). Most of innovation activities are conducted by private-sector firms, but market failures are likely to hamper firms from reaching the socially optimal level of R&D investment (Nelson, 1959; Arrow,1962).

One type of such market failure has to do with incomplete appropriability of R&D returns. Since the knowledge created by R&D activities is non-rival and can spill over to other entities, private returns from R&D investment become smaller than the social benefits. Another type of market failure is the problem of asymmetric information in the capital market. It is well known that the presence of asymmetric information raises the cost of funds coming from uninformed outside financiers. This is a general problem in finance, but the informational asymmetry is especially high for R&D activities because firms are reluctant to reveal their innovative ideas (Hall and Lerner, 2010).

To encourage R&D investment by private firms and move the level closer to the socially optimal level, many countries have improved their protection of intellectual property right and provided financial incentives for private R&D. The most common financial incentive policies are tax credit and direct subsidies. This paper contributes to the literature by examining large scale innovation subsidies policies implemented by the Chinese government to promote upgrading and transformation of the economy.

Second, this paper is related to the literature on the effects of public innovation incentives on private innovation activities. Many papers investigate whether public innovation subsidies increase the total R&D in the economy (crowding-in) or just substitutes private sector R&D (crowding-out) (David *et al*. 2000; Lerner, 2009), and they reach different conclusions (David *et al*., 2000; García-Quevedo, 2004). The impact of innovation subsidies seems to depend on many factors including time span considered, financial conditions of firms, history of obtaining subsidies, and size and sources of subsidies (Zúñiga-Vicente *et al*., 2014; Becker, 2015).

Some recent papers use the regression discontinuity approach to measure the impact of innovation subsidies more precisely. For example, by exploiting the mechanism used to grant the R&D subsidy programs, Bronzini and Piselli (2016) find a positive significant effect of subsides on the number of patents and the probability of applying for a patent. Howell (2017) finds that the early-stage R&D grants have statistically significant positive impacts on firms' patenting and revenue. She finds that these effects are particularly stronger for financially constrained firms.

Most relevant to this paper, a few papers examine the innovation subsidies by the Chinese government. Fang *et al*. (2018) finds that government innovation subsidies are positively associated with future innovation, especially after the anti-corruption campaign and departures of local government innovation officials. Dang and Motohashi (2015) estimate the effects of China's innovation subsidies on both patent quantity and quality. They find that these policy incentives increase the number of patents but deteriorate the quality measured by the scope of claims.

Finally, this paper contributes to the literature on the misallocations of economic resources and its effects on aggregate productivity. Misallocation of resources across firms can have important effects on aggregate total factor productivity (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). One potential source of misallocation is in granting of government innovation subsidies. If subsidies are granted preferentially to state-owned firms or politically connected firms, then the subsidies are misallocated and the aggregate productivity is depressed to the extent that the politically favored firms are not necessarily more innovative. Or if subsidies are granted to larger firms that would conduct innovative activities anyway, that may also be misallocation in the sense that smaller and younger firms that would benefit more cannot get the subsidies (González *et al*., 2005; Czarnitzki and Ebersberger, 2010; Cantner and Kösters, 2012; Becker, 2015). This type of misallocation may result in the persistence of market power of large firms and higher barriers to entry, and thus impeding the aggregate productivity growth (Acemoglu *et al*., 2017).

This paper's main finding that firms with political connections are more likely to obtain access to innovation subsidies but they do not exhibit higher quality innovations is consistent with other papers in the literature (Shleifer and Vishny, 1993, 1994; Faccio, 2006; Li *et al*., 2008). Perhaps more importantly, this paper further finds that, compared with state ownership, political connections are more influential in obtaining subsidies. Thus, the declined proportion of state ownership does not imply higher allocation efficiency if many firms continue to maintain political connections.

The paper is organized in the following way. The next section briefly discusses the background for China's innovation policy. We point out that the subsidies to encourage technological innovations have been and will continue to be a key tool for the policy. Section 3 introduces the Chinese Employer Employee Survey (CEES), which is the database that we use to examine the allocation and impacts of innovation subsidies. Section 4 examines the allocation of innovation subsidies among sample firms during the years from 2012 to 2015. Did firms that seem more likely to innovate receive the innovation subsidies? Or were the subsidies allocated mainly to State-Owned Enterprises (SOEs) and other politically connected firms? Section 5 asks what type of activities that subsidized firms undertook. Did subsidies really encourage innovations? Section 6 concludes.

2. China's Policies to Encourage Innovations

The Chinese economy has achieved a phenomenal growth over the last 40 years and now China accounts for 26.7% of the world's manufacturing value added in 2015 according to the World Bank data and ranked first in Deloitte Global Manufacturing Competitiveness Index in 2016. The Chinese government, however, realizes that the conditions that allowed the Chinese economy to grow rapidly are disappearing.

For example, China's low labor costs that supported the rapid growth are almost gone. According to CEES Research Team (2017), China's wage level is nearly the same as in Brazil and significantly greater than in other emerging markets (Malaysia, Thailand, Mexico, Vietnam and India). The projection on the future population growth does not look promising, either. According to National Bureau of Statistics of China, the birth rate is 12.43‰ in 2017 and the growth rate of working population (15-64 years old) has been negative since 2015. China's population is also aging quickly. According to the OECD statistics, the share of population older than 65 years old was 8.5% as late as 2011. This was much lower than the OECD average (14.9%) in that year, but the share is predicted to exceed 20% by 2036 and to be within 3% of the OECD average.

Favorable conditions for technological progress for China are also disappearing. As Chinese industries were technologically behind those in more advanced countries, China was able to rely on foreign technologies to upgrade the industries. Weak protection of intellectual property rights in China also helped by increasing the speed of dissemination of new technologies. The cost of weak intellectual property rights would have been diminished incentives for innovators to advance the technological frontier, but Chinese firms did not have capacity to innovate at least when the economy started to grow four decades ago. As the economy has grown and the industries has come closer to technological frontier, China has encountered the challenge of generating its own innovations. President Xi Jingping summarizes this challenge in his speech to the Chinese Academy of Sciences and the Chinese

Academy of Engineering as follows:[1]

> China's foundation for science and Technology innovation is still not firm. China's capacity for indigenous innovation, and especially original innovation, is still weak. Fundamentally, the fact that we are controlled by other in critical fields and key technology has not changed.

To keep competitiveness of manufacturing in the world, which is considered essential for China's growth, China needs to upgrade and transform its manufacturing to be more innovative and more efficient. Based on this idea, the Chinese government has been trying to encourage innovations by Chinese firms.

China's innovation policy has been mostly industrial targeting policy, which identifies several targeted industries and supports those industries through subsidies, tax breaks, and preferential (and subsidized) financing. For example, China's government targeted the new energy vehicle industry in early 2009 and started to promote the industry.[2] In June 2012, the State Council of China published the *Development Plan of Energy Saving and New Energy vehicle industry (2012-2020)* to further boost the technology innovation and the manufacturing of new energy vehicles.[3] According to the Ministry of Finance of China, from 2009 to 2015, the total amount of subsidies to new energy vehicle industry given by the central government amounted to about 33.4 billion RMB.[4] In addition to the central government, local governments also provide matching subsidies that amount to 30% to 100% of the central government subsidies.

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[1] *Xi Jinping: Speech at the 17th Conference of the Chinese Academy of Sciences and 12th Conference of the Chinese Academy of Engineering* (习近平：在中国科学院第十七次院士大会、中国工程院第十二次院士大会上的讲话), Chinese Communist Party News, June 9, 2014, http://cpc.people.com.cn/n/2014/0610/c64094-25125594.html (Accessed October 23, 2018), translated and cited by European Union Chamber of Commerce in China (2017).

[2] "New Energy" vehicles include electric vehicles and plug-in hybrid engine vehicles.

[3] *The Development Plan of Energy Saving and New Energy vehicle industry (2012-2020)* (国务院印发节能与新能源汽车产业发展规划:2012-2020 年), The State Council of China, July 10, 2012, http://www.nea.gov.cn/2012-07/10/c_131705726.htm (Accessed October 23, 2018).

[4] *The Notification on the Disclosure of the Budget and Final Accounts of Local Governments and the Investigation of the Subsidies on the Promotion of New Energy Vehicles* (财政部关于地方预决算公开和新能源汽车推广应用补助资金专项检查的通报), The Ministry of Finance of China, September 8, 2016, http://www.gov.cn/xinwen/2016-09/08/content_5106603.htm (Accessed October 23, 2018).

Helped by the promotion policy, the new energy vehicle industry grew very rapidly. The production of new energy vehicles increased more than 100 times from 7,200 units in 2010 to 794,000 units in 2017. By the end of 2017, China has become the country with the largest stock of new energy vehicles.[5]

The policy has turned out to be too successful. The *Development Plan of Energy Saving and New Energy vehicle industry (2012-2020)* set the goal of 2 million units per year by 2020 as the production capacity of new energy vehicles. According to China Automobile Dealers Association, however, the total capacity of 200 completed new energy vehicle projects already reached 20 million units per year by June of 2017, which is 10 times larger than the goal. The industry's capacity clearly exceeds the demand. Many manufacturers make profits only because they are subsidized: they would suffer losses if the amounts of subsidies are reduced substantially.

The policy to subsidize the new energy vehicle industry also created more horrendous cases of subsidy deception. Some manufacturers that are supposed to be making new energy vehicles received subsidies based on fake technical specifications. According to the investigation of the Ministry of Finance of China, 93 new energy vehicle companies received 9.27 billion RMB of subsidies that they should not have received.[6]

The latest of China's industry policy to promote innovations is Made in China 2025 (MIC 2025). Early in 2013, the Ministry of Industry and Information Technology and the Chinese Academy of Engineering (a think tank with ministerial-level rank) started a series of studies for a new 10-year national program titled "China's Manufacturing Power Strategy." In 2014, Vice Premier Ma Kai expressed his full support and urged a swift formulation of the program. On May 8 in 2015, *Made in China 2025* was officially released by China's State Council and

[5] *Global EV outlook 2018*, OECD/IEA, https://www.iea.org/publications/freepublications/publication/GlobalEVOutlook2017.pdf (Accessed October 23, 2018).

[6] *9.27 Billion RMB Subsidies on 76 Thousand New Energy Vehicles are Cheated* (7.6 万辆新能源车骗补 92.7 亿元), Securities Daily, September 9, 2016, http://epaper.zqrb.cn/html/2016-09/09/content_210081.htm (Accessed October 23, 2018).

authorized by the Premier Li Keqiang.[7] MIC 2025 program is aimed at transforming China from a low value-added manufacturing giant into a world high value-added manufacturing power.

Responding to the nationwide program of MIC 2025, provincial and city governments announced their programs that contribute to MIC 2025. By 2017, the central government selected about 30 cities as demonstration pilot cities that have outstanding programs. The demonstration pilot cities include six cities in Guangdong province and one city in Hubei province (Wuhan), the two provinces covered by the database we use for statistical analysis below. To facilitate the actual implementation of MIC 2025, eleven detailed industrial policies (at the state level) were also announced in 2017.[8]

MIC 2025 targets ten industries including (1) next generation information technology, (2) high-end numerical control machinery and robotics, (3) aerospace and aviation equipment, (4) maritime engineering equipment and high-tech maritime vessel manufacturing, (5) advanced rail equipment, (6) energy-saving and new energy vehicles, (7) electrical equipment, (8) new material, (9) biomedicine and high-performance medical devices, and (10) agricultural machinery and equipment. The new energy vehicle industry made the list despite some problems that we pointed out above and received 38.1 billion RMB of subsidies in 2016 alone. These industries collectively cover nearly 40 percent of China's entire manufacturing value-added according to Rhodium Group analysis (U.S. Chamber of Commerce, 2017, p.10). The announcement of MIC 2025 was followed by the release of *Made in China 2025 Major Technical Roadmap* (2015), also known as *Green Book*. Formulated by the National Advisory Committee on Building a Manufacturing Power Strategy, *Green Book* specifies explicit targets

[7] *Notification on the Printing and Distribution of Made in China 2025* (国务院关于印发《中国制造 2025》的通知), The State Council of China, May 8, 2015, http://www.gov.cn/zhengce/content/2015-05/19/content_9784.htm (Accessed, October 23, 2018). Also, *Made in China 2025* is the executive summary document of China's Manufacturing Power Strategy, but it has been used to refer to the entire set of policies especially outside China.

[8] *A Planning System with 1+X Policies for Made in China is Released* (《中国制造 2025》"1+X"规划体系全部发布), Ministry of Industry and Information Technology of China, February 10, 2017, http://www.miit.gov.cn/newweb/n1146295/n1146562/n1146650/c5483427/content.html (Accessed October 23, 2018).

on growth rate and market share, and details various policy assistances for each targeted industry and its subsectors.

Numerous policy tools will be used to achieve the goals of MIC 2025. Subsidies including preferential access to cheap capital will be provided to the firms in the targeted industries. Many expect the Chinese government will require foreign firms in the targeted industries to transfer technology to Chinese firms before they enter the Chinese market. Since China is not a party to the WTO Agreement on Government Procurement, favoring domestic firms in government procurement in the targeted industries is another policy tool available for China.

Of these, the most important policy tools that China will certainly use are subsidies to innovative firms in the targeted industries. For example, *Several Opinions on Finance to Support Industry Stable Growth, Restricting, And Improving Profit*, issued by seven ministries and the People's Bank of China on February 16, 2016, encourages banks to provide financial support to industries including those targeted in MIC 2025.[9] Similarly, the *Action Plan to Improve Information Sharing and Promoting Industry and Finance Cooperation*, jointly issued by the Ministry of Industry and Information Technology (MIIT), the People's Bank of China (PBOC) and the China Banking Regulatory Commission (CBRC) in March 2016, calls for the banking industry to support key enterprises and projects that are important for the MIC 2025.[10] *Made in China 2025 Strategic Cooperation Agreement* by MIIT and ICBC is signed on February 9, 2018. ICBC promised to provide at least 500 billion RMB of financial support to the transformation and upgrading of MIC 2025 targeted manufacturing in the next 5 years.[11] Thus,

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[9] *Several Opinions Regarding Finance to Support Stable Growth of Industry, Restructuring and Improving Profit* (关于金融支持工业稳增长调结构增效益的若干意见), The State Council Information Office, www.scio.gove.cn, February 24, 2014, http://www.scio.gov.cn/xwfbh/xwbfbh/yg/2/Document/1469592/1469592.htm (Accessed October 23, 2018).

[10] *Action Plan to Improve Information Sharing and Promoting Industry and Finance Cooperation* (三部委关于印发《加强信息共享 促进产融合作行动方案》的通知), Ministry of Industry and Information Technology of China, March 3, 2016, http://www.miit.gov.cn/n1146290/n4388791/c4655349/content.html (Accessed October 23, 2018).

[11] *Made in China 2025 Strategic Cooperation Agreement* (工业和信息化部与工商银行签订实施《中国制造2025》战略合作协议), Ministry of Industry and Information Technology of China, February 9, 2018, http://www.miit.gov.cn/n973401/n1234620/n1234621/c6058413/content.html (Accessed October 23, 2018).

our examination of allocation and impacts of innovation subsidies using the data right before the formal start of MIC 2025 can produce important information to gauge the success of MIC 2025.

3. Data

The data used in this study come from the China Employer Employee Survey (CEES), which is a collaborative project between Wuhan University, Hong Kong University of Science and Technology, Stanford University, and the Chinese Academy of Social Science. The survey was conducted in two waves in 2015 and 2016. As is shown in Table A1, the 2015 wave covered 573 firms and 4,838 employees matched with the firms in 13 cities and 19 counties in Guangdong province. The 2016 wave expanded the survey to Hubei province and covered 1,122 firms and 9,103 employees in 26 cities and 39 counties. The sample firms come from the *Third Economic Census*, which was conducted in early 2014. Sampling was conducted in two stages, each using probability proportionate-to-size (PPS) sampling, with size defined as the number of employees involved in manufacturing. Thus, the firm sample is representative of the employment size of firms in China.[12]

CEES contains the information on the technology and innovation subsidies, which are the central subsidies in the MIC 2025 and what we will examine in this paper. CEES asks each firm if the firm received various subsidies. Four of the subsidies (environmental protection technology subsidies, new energy technology subsidies, high-tech subsidies, and technological upgrading subsidies) are considered to be the innovation subsidies. Information on innovation subsidies is captured in both waves 2015 and 2016. In wave 2015, CEES asked whether a firm gained these subsidies during 2012~2014. In wave 2016, CEES had two different types of questionnaires, one is for firms that participated in the 2015 wave and asked whether they received the innovation subsidies in the previous year (2015), the other is for the new firms that

[12] For more details on the CEES, see CEES Research Team (2017). In the first stage, 20 county-level districts were randomly sampled in each province, with probabilities proportionate to manufacturing employment size in each district. In the second stage, 50 firms were sampled in each district as a target sample, again with probabilities proportional to employment in each firm. Enumerators then started to visit the 50 firms in sequence and stopped when they received responses from 36 eligible firms (that had production activities in the sampled district) or when they finished visiting all the 50 firms.

joined the 2016 wave and asked whether they received the innovation subsidies during 2012~2015. We combine these three kinds of questionnaires on innovation subsidies in two waves and construct a dummy variable indicating whether a firm received innovation subsidies in any year between 2012 and 2015. We use this as a main variable in our statistical analysis below.

In examining the allocation of technology and innovation subsidies, a key question that we ask is whether the subsidies are allocated primarily to the firms that show greater promise to be innovative or to those firms that are politically favored. One obvious way to define politically favored firms to use the ownership by the state. CEES has information of state ownership of each firm, and we define a state owned enterprise (SOE) to be a firm that is majority owned by the state.

State ownership is one obvious way that a firm is politically favored, but there are some other channels that the firms can use to establish close relation with the government. As Li *et al*. (2006) points out, the Chinese political system consists of four branches. People's Congress (PC) is the legislative branch, (central and local) governments are the administrative branch, Supreme Court and People's Courts at local levels form the judicial branch, and Chinese People's Political Consultative Conference (CPPCC) is the democratic supervision branch. Chinese firms can obtain political connection to the government by acquiring seats for their CEOs in PC or (more often) CPPCC.

Thus, we use political connection through PC or CPPCC membership as another proxy for political favoritism in our analysis of allocation of technological subsidies. We consider a firm politically connected if the CEO or the owner of the firm is a member of PC or CPPCC (national or local level).

To investigate the impacts of the innovation subsidies on the innovative activities of corporations, we examine five potential measures of corporate innovation in CEES. First is the 0-1 dummy variable that takes 1 if the firm were successfully granted patents (either in China or abroad) between 2012 and 2015. Second is the total number of patents granted between 2012 and 2015. Since the patents include those for designs of product rather than technology related in a narrow sense, we consider the number of invention patents as the third dependent variable. The fourth variable is number of patents granted in foreign countries (mainly the U.S.). Because the Chinese patent system allows some marginal innovations and design tweaks, the patents granted abroad are considered much higher quality ones than those granted in China. Finally, we consider the 0-1 dummy that takes 1 if the firm introduced any new products between 2012 and 2015.

We also examine whether some corporate performance measures that can be indirectly linked to innovations are influenced by the innovation subsidies. The performance measures that we consider are grouped into three types: (1) productivity, (2) market share, and (3) profitability.

First, we measure productivity in two ways. One is a proxy of labor productivity, which is calculated by dividing total sales by the number of employees. The other is total factor productivity (TFP). We calculate TFP for each firm by estimating value-added production function separately for each industry to control for the industry heterogeneity. We follow the approach developed by Levinsohn and Petri (2003) to correct for potential bias in estimation of production function caused by correlation between productivity shocks and changes in input use.

The market share is measured using sales. The market share in our database is a categorical variable. It takes 1 if the market share is less than or equal to 1%, 2 if it is between 1% and 10%, 3 if it is between 11% and 50%, and 4 if it is above 50%.

We use two proxy variables for profitability. One is profit rate calculated by dividing corporate profits by total sales. The other is the loss dummy which takes 1 if the firm reports annual losses for any year between 2013 and 2015.

Finally, we include several control variables that may influence firm's likelihood of receiving innovation subsidies, innovation outcomes, and economic performance in our regression analyses. The control variables are: number of employees (in log), firm age, firm's export (0-1 variable that takes 1 for an exporting firm), R&D intensity (calculated as the ratio of the R&D expenses to total sales), CEO's education level (number of years in school), CEO's work experience (number of years in work), and whether CEO has MBA or has participated in executive MBA programs. All the regression models that we estimate also include one province dummy that takes 1 for firms in Hubei Province and 0 for those in Guangdong Province and 26 industry dummies.

Table 1 presents the summary statistics of the variables that we use. The table shows that just 7% of the firms in our sample are majority state-owned. There are more firms that are politically connected. In total, 23% of the firms are politically connected. The 14% of the firms have their CEOs or owners in PC and 13% have CEOs or owners in CCPPC.

Table 2 shows a cross tabulation of the political connection variable and the state ownership. The majority of the firms in our sample (771 firms or 72.0% of the sample) are not state-owned and have no political connections. Small number of firms (27 firms or 2.5% of the sample) are state-owned and have political connections. There are some SOEs (50 or 4.7% of the sample) that are not politically connected according to our definition. Finally, there are substantial number of non-SOEs (223 or 20.8% of the sample) that are politically connected.

4. Allocation of innovation subsidies

This section examines whether state ownership and political connection matter for the likelihood of receiving innovation subsidies. Table 3 shows that 51.9% of politically connected SOEs receive innovation subsidies, while the proportion of politically connected non-SOEs that receive the subsidies is 29.6%. Similarly, the proportion of non-politically connected SOEs that receive the innovation subsidies (36%) is higher than the proportion of non-politically connected non-SOEs (19.6%). Thus, this simple comparison suggests that innovation subsidies are allocated more to SOEs. The table also shows, given the state-ownership, politically connected firms are more likely to receive innovation subsidies than non-politically connected firms.

Thus, SOEs and politically connected firms appear more likely to receive innovation subsidies, but the simple comparison of means does not prove that these firms receive favorable treatments by the government because of their relation to the government. This may just reflect other differences between SOEs or politically connected firms and the others. For example, SOEs and politically connected firms may be concentrated in the industries with high R&D intensity for some reason and those industries may be more likely to receive innovation subsidies. To control for the other factors that may influence the likelihood of obtaining innovation subsidies, we estimate simple Probit regression models.

The dependent variable in the regressions is the 0-1 variable that takes one when the firm receives any innovation subsidy between 2012 and 2015. The main explanatory variable is the political connection dummy that takes one when the firm is politically connected and the SOE dummy that takes one when the firm is state-owned. We also include all the control variables as well as the province dummy and the industry dummies discussed above.

Of the firms in the CEES database, 1,053 firms have information on all the major variables of our interest: innovation subsidies, political connection, state ownership, province, and industry. For 924 of those, the database has information on all the control variables. We use this set of 924 firms as the full sample for the regression analyses below.

Table 4 presents the estimation result of Probit models for determinants of innovation subsidies. Each cell reports the average marginal effect of the explanatory variable (row) in the model (column) and its standard error in the parentheses. Model 1 includes just industry dummies, province dummy, and the state ownership dummy without any other controls. The estimation result shows that SOEs are more likely to receive the innovation subsidies. This result is consistent with what other researchers found (König *et al.*, 2018; Tan *et al.*, 2016; Herrala and Jia, 2015; Ferri and Liu, 2010). When the controls are added (Models 2 and 3), however, the coefficient estimate on the SOE dummy becomes substantially smaller and loses statistical significance. Thus, controlling for various attributes of firms and managers, the majority state ownership is not correlated with the likelihood of getting the innovation subsidies.

Model 4 includes the political connection dummy instead of the SOE dummy. The political connection clearly increases the probability of receiving the innovation subsidies.

When the set of control variables are added (Models 5 and 6), the coefficient estimate on the political connection dummy becomes smaller but it is still statistically significant. The point estimate in Model 6 suggests that having political connection increases the probability of receiving innovation subsidies by 8.8%. Since about 23% of the sample receive innovation subsidy, the estimated impact of political connection is also economically significant.

Models 7, 8, and 9 include both political connection and SOE dummies as major explanatory variables. When the control variables are not included (Model 7), both political connection and SOE dummies enter the regression model significantly with positive signs. When the control variables are added (Models 8 and 9), the coefficient on the SOE dummy is not statistically significant anymore while the political connection continues to be positive and statistically significant.

Model 10 adds the interaction term of political connection and SOE, although the marginal effect of the interaction term is not reported in the table. The point estimate of the marginal effect of the interaction term is negative but not significant (-0.220 with standard error of 0.406), which indicates political connection is positively related to innovation subsidies no matter ownership is SOE or not.

Examining the estimated coefficients on the industry dummies (not reported in table), we find that the coefficients on the dummies for industries targeted in MIC 2025 have large positive values in all the specifications in the table. When we replace the industry dummies with a single dummy variable that takes 1 if a firm is in one of the MIC targeted industries and 0 otherwise, the coefficient is positive and statistically significant in all the specifications without changing other results substantially.[13]

Taken together, the results in Table 4 suggest that the innovation subsidies are more likely to be allocated to SOEs and political connected firms. Unless state ownership or political connection is perfectly correlated with capacity to innovate, the result means that there are some firms that do not receive the innovation subsidies but have higher capacity to innovate than some

[13] MIC 2015 targeted industries are defined according to the *Green Book*, and include the following 2-digit industries, 13, 14, 25, 26, 27, 28, 34, 35, 36, 37, 38, 39 and 40.

firms that receive the subsidies because of their relationship to the government. In this sense, the innovation subsidies are allocated inefficiently.

Table 4 also shows that the political connection is more important than state ownership in determining the likelihood for a firm to receive the innovation subsidies. Even when all the control variables and the SOE dummy are included at the same time (Model 9), the political connection increases the probability of receiving the innovation subsidy significantly. The SOE dummy on the other hand loses the explanatory power completely when the control variables are introduced.

We also find that the innovation subsidies are allocated preferentially to the industries targeted by MIC 2025 at least by 2015. These subsidies will most likely continue to be the most important tools in implementing MIC 2025.

5. Impacts of innovation subsidies

This section examines the impacts of the innovation subsidies. We first estimate regression models that relate innovation performance of a firm to whether the firm received innovation subsidies with the set of control variables. Since there may be time lags between receiving innovation subsidy and the subsidy resulting in innovation (or influencing profitability) of the firm. Unfortunately, our data do not allow us to address the timing issue. All we can tell is the cross-sectional correlation between subsidies and innovation (or profitability/productivity). We consider five potential measures of corporate innovation as we discussed above.

We estimate the regression models in this section by OLS (Ordinary Least Squares). Since some of the dependent variables are 0-1 variables, the OLS specification is not literally correct as some predicted values will be below 0 or above 1. As Wooldridge (2010, p563) notes, we should consider the OLS estimation in such case as a linear projection of the probability that the dependent variable takes 1 onto the space spanned by the explanatory variables.

Table 5 shows the results. Model 1 examines whether the firms that got innovation subsidies are more likely to have patents. The estimated coefficient on the innovation subsidies dummy is positive and statistically significant. The point estimate suggests that subsidies increase the probability that the firm receives patents by about 29%. There are some notable results on the coefficients on control variables. The positive coefficient on employment suggests that large firms are more likely to have patents. As many would expect, R&D intensive firms are more likely to have patents. Firms with CEO with high educational achievement and MBA are more likely to receive patents, but CEO's work experience does not seem to matter.

Model 2 adds the political connection dummy and the SOE dummy. The coefficient on the political connection dummy is positive and statistically significant. The coefficient on the SOE dummy is not significantly different from zero. Thus, even given the presence or absence of innovation subsidies, the political connection provides an additional advantage on the likelihood of getting patents, but the state ownership does not. Political connection again seems more important than state ownership.

Models 3 and 4 consider the total number of patents that a firm receives as the measure of innovation performance. The results are similar to those for Models 1 and 2. The innovation subsidies tend to increase the number of patents. The only difference is in Model 4 the political connection and the SOE have additional effects of increasing the total number of patents, as suggested by the positive and significant coefficients on political connection and SOE dummies.

Models 5 and 6 focuses on invention patents. China's patent system grants three types of patents: invention, utility model and design. Only applications for invention go through substantive examination for utility, novelty, and non-obviousness. Thus, it is widely recognized that innovation patent is of the highest quality among Chinese patents. According to the Patent Annual Report by State Intellectual Property Office of China, in 2016, among total patents in force (3,464,824, stock number), invention patents account for only 28.2%.

The regression results for invention patents are quite similar to those in Models 3 and 4.

Even when we limit our attention to the invention patents, innovation subsidies tend to increase the number of patents. In addition to this, both political connection and state ownership further increase the number of invention patents.

Even the invention patents in China are considered to be of lower quality compared to the patents in other jurisdictions such as the U.S., Japan and EU. Recently there have been increasing number of patent filing abroad by Chinese inventors. World Intellectual Property Organization (2017, p.34) points out “Filing abroad reflects the globalization of intellectual property (IP) protection and a desire to commercialize technology in foreign markets. The costs of filing abroad can be substantial, so the patents for which applicants seek international protection are likely to confer higher values.”

The foreign patents originated in China are much higher quality than patents filed in China, but they are still of lower quality than the patents originated in other countries. For example, Boeing and Muller (2016) find that among PCT (Patent Cooperation Treaty) patents, those originated in China score lower than those originated in the U.S., Korea, Germany and Japan on the quality measure based on forward citations in International Search Reports. Squicciarini *et al*. (2013) find that among patents filed at European Patent Office (EPO), patents originated in China have lower score than the world average in terms of patent scope, family size, claims, and radicalness.

We examine the number of patents filed and granted in foreign countries, which are considered to be at least higher quality than domestic patents in China, in Models 7 and 8. Here we get a very different result. The coefficient on the innovation subsidy dummy is still positive but small and only marginally significant. There are no additional effects of political connection or state ownership. The results suggest that although innovation subsidies increase patenting in China they often fail to lead to patents in foreign countries.

The distribution for the number of patents is often considered to have a fat tail. If this is the case, OLS estimator is inconsistent. To examine how serious this problem can be, we estimated Models 3 through 8 by using Poisson regression models. The results, which are reported in Table B1, are nearly identical to the OLS results in Table 5.

Finally, Models 9 and 10 consider whether firms with innovation subsidies are more likely to introduce new products. The coefficient on innovation subsidy dummy is positive, suggesting the subsidies indeed increase the probability of introducing new products. There are no additional effects of political connection or state ownership.

The analysis in Table 5 assumes that the impact of innovation subsidy does not depend on firm characteristics such as size. We have repeated the same analysis relaxing this assumption and considering the possibility that the impacts are different between large and small firms. Table B2 contains the results of regressions that include the interaction term between innovation subsidy dummy and firm size. For some specifications (Columns 2 through 4), we find the interaction term is statistically significant. To see how the impact differs between small firms and large firms, Figure B1 shows the predicted values of the dependent variable as a function of firm size for subsidized firms and non-subsidized firms separately. We calculate the predicted value assuming all the explanatory variables other than innovation subsidy dummy and firm size take the average values for the entire sample. The range of firm size is limited to the middle 90% of the observations, so that we can compare the typical firms in the sample. The graph also includes 95% confidence intervals for selected value of firm size. Panels A and B of Figure B1 show that the result that the firms that receive innovation subsidies tend to have more patents in total and more invention patents come mostly from medium to large firms. Small firms do not have many patents and innovation subsidy does not seem to matter for them. For the number of foreign patents (Panel C), the difference between subsidized and non-subsidized firms is less clear even for large firms, which is consistent with the result in Table 5.

One potential concern of our analysis is that subsidized firms and non-subsidized firms differ so widely in many aspects beyond the innovation subsidy that the comparison is difficult. Although include many control variables that control for the impacts of those variables (linearly), we cannot control all the factors that are systematically different between two groups. To address this concern, we tried comparison based on propensity score matching. The results are summarized in Appendix C, but we get qualitatively similar results as those in Table 5. The only substantial difference is the estimated effect of innovation subsidy on the probability to introduce new products. Although it is significantly positive in Table 5, the propensity score matching analysis fails to detect the impact of innovation subsidy on the new product dummy.

Table 6 reports the regression analyses of the impacts of innovation subsidies on other performance variables such as productivity, market share, and profitability. We again include the same set of control variables as in the analyses above as well as the province dummy and the industry dummies.

Looking at Table 6, we find that the innovation subsidy does not influence these performance variables except for the productivity measured as sales divided by employment, where the impact of subsidy is positive but the statistical significance is only marginal. This suggests that the innovation subsidies do not make the recipient firms more productive, profitable, or increase the market share. Although the subsidies tend to increase the patenting at least in Chinese patent office and increases the likelihood of new products, they do not seem to help the firms improving other performances (with a potential exception of sales/employment).

The SOE and political connection dummy seem to influence some of these performance measures. SOEs tend to have higher productivity measured in sales per employment (Model 1), but does not have significant influence on the other four performance measures. Political connection, on the other hand, tends to increase productivity measured in sales per employment, market share, and reduces the probability of experiencing loss. The findings here are again consistent with the view that political connection is more important discriminant of Chinese firms than state ownership.

We again considered the possibility that the impact of innovation subsidy depends on the size of firms by adding the interaction term to regression models. The result is reported in Table B3. The interaction term comes in significantly only when we consider market share as the dependent variable. The overall impact of innovation subsidy on the market share, however, is insignificant regardless of the size, as Figure B2 shows.

We also conducted the propensity score matching analysis for the impacts of innovation subsidy on productivity, profitability, and market share. As the result reported in Appendix C shows, the results are very much the same.

In summary, we find that the innovation subsidies indeed increase the total number of patents granted and the likelihood of introducing new products. The number of patents granted abroad, however, does not increase significantly with the innovation subsidies. These results suggest that the innovation subsidies may be encouraging only incremental technological improvement and new products that are not drastically different from old products. The innovation subsidies do not seem to generate truly innovative patents that are granted in foreign countries with stronger patent systems. Our result is consistent with the findings by Dang and Motohashi (2015), which examined the patent data in China. They find that the subsidy programs that they examine actually encourage firms to narrow the scopes of patents to make it easier to obtain patents.

The innovation subsidies also fail to improve the bottom line performance of the recipient companies (with an exception for sales per employment). This suggests that the patents and new products that are encouraged by the subsidies do not add much to productivity or profitability.

6. Discussion

As the catch-up phase of China's economic growth is coming to an end, the Chinese government has been trying to transform the Chinese economy from a developing economy that depends on foreign technologies to an advanced economy that is supported by indigenous innovations. The main tools of China's industry policy to promote innovations have been various subsidies. This paper assesses the success of China's innovation policy by studying the impacts of innovation subsidies using data from the CEES. We make three important findings. First, the innovation subsidies are allocated preferentially to politically connected firms. Politically connected firms are not necessarily state owned and not all SOEs are politically connected. For the allocation of subsidies, we find political connection is a more important determinant than state ownership. Because politically connected firms are not necessarily more innovative firms, the result suggests inefficiency of the allocation of the innovation subsidies.

Second, firms that receive subsidies file more patents and are more likely to introduce new products, but do not necessarily file more patents outside China. Since the quality of patents granted in China are lower than those in foreign jurisdictions, the result suggests the innovation subsidies often encourage the firms to come up with incremental changes and not truly innovative technologies.

Third, the firms that receive innovation subsidies do not show higher productivity, more profitability, or larger market shares. Thus, the innovation subsidies do not seem to help the bottom lines of the recipient firms.

Overall, our findings suggest that the allocation of innovation subsidies is inefficient, that the subsidies encourage only incremental innovations and not radical ones, and that the subsidies do not help the bottom lines. These make one doubt the effectiveness of China's innovation policy so far.

In a recent paper, Fang, Lerner, Wu, and Zhang (2018) examined similar questions about the relation between politics, government subsidies, and innovation in China. Using the data for Chinese firms listed in Shanghai and Shenzhen A-share markets, they find that the allocation of government subsidies became more efficient in the sense that subsidies are correlated with firm's innovative capacity rather than political consideration, following the anticorruption campaign under Chairman Xi and in the regions where local government officials changed. They find that the subsidies also became more positively correlated with future innovation.

Thus, their findings paint a more promising picture for the future of China's innovation policy than what our results suggest. Both allocation and effectiveness of government subsidies seem to have improved recently. There are some differences between their sample firms and our sample firms, which at least partially may explain the difference. Their sample includes only firms publicly listed in Shanghai and Shenzhen, while our sample includes both listed and unlisted firms but in two provinces. They identify the firms that are likely to be receiving political favors by looking at the entertainment expenses reported by the firms, while we check the CEO's membership in PC and CPPCC. They study panel data while our examination is limited to cross-sectional variation, which prevents us from investigating the change overtime. As far as we examine the data on a wide range of firms in Guangdong and Hubei, however, we still find the political connection (measured in political membership of CEOs) still mattered for the allocation of innovation subsidies even after the anticorruption campaign started.

Our findings have important implications for the attempts by the Chinese government to stimulate innovations. Chinese government seems to believe that the industrial policies such as innovation subsidies will transform China into a world leader in innovations and allow China to continue economic growth. Many critics outside China view these attempts as manifestation of China's traditional state-led economic development that not only survived to today but rather got intensified. Our results suggest that these industrial policies are not effective in promoting innovation and can distort the allocation of economic resources. If the Chinese government wishes to promote innovation in the long run, phasing out these preferential policies to create fair and competitive business environment for all economic players is likely to be more effective.

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Table 1. Descriptive Statistics of Variables

Variable	N	Mean	SD
Technological innovation subsidy dummy	1,189	0.23	0.42
Political connection			
People's Congress (PC) member	1,086	0.14	0.35
Chinese People's Political Consultative Conference (CPPCC) member	1,083	0.13	0.34
PC or CPPCC	1,087	0.23	0.42
Ownership			
SOEs	1,202	0.07	0.26
Private	1,202	0.68	0.47
HMT	1,202	0.18	0.38
Foreign	1,202	0.07	0.26
Firm's attributes			
Firm age	1,202	12.31	7.59
Firm size (Employment)	1,114	827.4	2,765.6
Exporter	1,117	0.43	0.49
R&D sales ratio	1,030	0.02	0.06
Entrepreneur's attributes			
Years of schooling	1,090	14.45	3.08
Industry working experience	1,057	20.74	10.25
CEO has MBA	1,074	0.3	0.46
Province			
Hubei	1,208	0.48	0.50
MIC targeted industries	1,188	0.46	0.50
Innovation			
Patent dummy	1,108	0.4	0.5
Total No. of patents	1,108	33.4	319.1
Total No. of invention patents	1,097	13.9	167.4
Total No. of foreign patents	1,081	4.3	76.5
New product dummy	1,109	0.421	0.494
Corporate performance			
Labor productivity (sales/employment)	1,098	76	182
TFP in log	848	3.109	2.343
Market share			
≤1%	1,143	0.207	0.406
1% ~ 10%	1,143	0.317	0.465
11% ~ 50%	1,143	0.270	0.444
≥ 50%	1,143	0.206	0.404
Profit rate (profit/sales)	1,066	0.041	0.120
Loss dummy	1,066	0.174	0.380

Table 2. Tabulation of Political Connections and Ownership

	Without Political Connections		With Political Connections		Total	
	No.	Row %	No.	Row %	No.	Row %
Non-SOEs	771	77.6	223	22.4	994	100
SOEs	50	64.9	27	35.1	77	100

Table 3. Innovation Subsidies by State Ownership and Political Connections

	SOEs		Non-SOEs		Mean difference (SE)
	# of Obs.	Mean	# of Obs.	Mean	
With political connections	27	0.519	223	0.296	-0.223** (0.094)
Without political connections	50	0.360	771	0.196	-0.164*** (0.059)
Mean difference (SE)	-0.159 (0.118)		-0.100*** (0.031)		

Table 4. Probit Regressions of Innovation Subsidies on Political Connections and Ownership

	Dependent variable: Technological innovation subsidy dummy										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	Original
SOE	0.189***	0.0511	0.0431				0.163***	0.0469	0.0404	0.0457	0.254
	(0.0623)	(0.0542)	(0.0529)				(0.0624)	(0.0549)	(0.0534)	(0.0549)	(0.265)
Political Connection				0.187***	0.101***	0.0884***	0.179***	0.100***	0.0879***	0.0895***	0.393***
				(0.0342)	(0.0316)	(0.0320)	(0.0343)	(0.0316)	(0.0321)	(0.0321)	(0.133)
SOE*Political Connection											-0.220
											(0.406)
Firm's attributes											
Employment in log		0.0563***	0.0435***		0.0542***	0.0429***		0.0523***	0.0414***	0.0414***	0.185***
		(0.00888)	(0.00952)		(0.00876)	(0.00942)		(0.00899)	(0.00961)	(0.00961)	(0.044)
Firm age in log		0.0607***	0.0611***		0.0551***	0.0581***		0.0526***	0.0560***	0.0560***	0.250***
		(0.0202)	(0.0207)		(0.0202)	(0.0207)		(0.0203)	(0.0208)	(0.0207)	(0.093)
Export		0.0329	0.0308		0.0319	0.0318		0.0334	0.0332	0.0336	0.150
		(0.0287)	(0.0289)		(0.0280)	(0.0282)		(0.0280)	(0.0282)	(0.0281)	(0.125)
R&D sales ratio		1.766***	1.595***		1.688***	1.537***		1.682***	1.535***	1.535***	6.843***
		(0.351)	(0.323)		(0.339)	(0.314)		(0.335)	(0.311)	(0.310)	(1.446)
Entrepreneur's attributes											
Years of schooling			0.00950**			0.0102**			0.00998**	0.00988**	0.044**
			(0.00450)			(0.00453)			(0.00452)	(0.00452)	(0.020)
Working experience			0.000406			-0.0000711			-0.000118	-0.000116	-0.001
			(0.00126)			(0.00128)			(0.00128)	(0.00128)	(0.006)
CEO has MBA			0.0660**			0.0501*			0.0504*	0.0511*	0.228*
			(0.0270)			(0.0270)			(0.0270)	(0.0270)	(0.121)
2-digit industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.100	0.230	0.244	0.121	0.240	0.251	0.130	0.241	0.252	0.252	0.252
N	924	924	924	924	924	924	924	924	924	924	924

Note: Interaction term of political connection dummy and state ownership is only included in the last column. Average marginal effects in cells and robust standard errors in parentheses.

Marginal effect for dummy variable is the discrete change from 0 to 1. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 5. OLS Regressions of Innovation Performance on Innovation Subsidy

	Dependent variables: Innovation performance									
	Patent dummy		Total No. of patents in log		Total No. of invention patents in log		Total No. of foreign patents in log		New product dummy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Innovation subsidy	0.293***	0.283***	1.055***	1.006***	0.498***	0.461***	0.139*	0.130*	0.183***	0.178***
	(0.040)	(0.040)	(0.129)	(0.128)	(0.100)	(0.099)	(0.073)	(0.073)	(0.044)	(0.045)
SOE		0.085		0.538***		0.576***		-0.024		-0.005
		(0.057)		(0.199)		(0.190)		(0.127)		(0.068)
Political Connection		0.069**		0.314***		0.174*		0.088		0.044
		(0.034)		(0.111)		(0.092)		(0.067)		(0.041)
Firm's attributes										
Employment in log	0.033***	0.029**	0.257***	0.234***	0.173***	0.153***	0.053*	0.051*	0.025*	0.024*
	(0.011)	(0.011)	(0.043)	(0.042)	(0.037)	(0.036)	(0.027)	(0.027)	(0.014)	(0.014)
Firm age in log	0.043*	0.036	0.081	0.044	0.086**	0.054	0.013	0.010	-0.007	-0.008
	(0.024)	(0.024)	(0.061)	(0.062)	(0.042)	(0.043)	(0.033)	(0.032)	(0.027)	(0.027)
Export	0.063*	0.067*	0.187*	0.208**	-0.007	0.012	0.093*	0.095*	0.094**	0.095**
	(0.035)	(0.035)	(0.100)	(0.099)	(0.078)	(0.077)	(0.054)	(0.055)	(0.041)	(0.041)
R&D sales ratio	2.132***	2.139***	6.914***	6.971***	2.615**	2.698**	1.465*	1.448*	1.141**	1.134**
	(0.595)	(0.582)	(1.661)	(1.601)	(1.243)	(1.195)	(0.824)	(0.835)	(0.551)	(0.549)
Entrepreneur's attributes										
Years of schooling	0.016***	0.016***	0.033**	0.032**	0.027**	0.026**	0.018**	0.019**	0.017***	0.017***
	(0.005)	(0.005)	(0.016)	(0.016)	(0.013)	(0.013)	(0.008)	(0.008)	(0.006)	(0.006)
Working experience	0.002	0.001	0.008*	0.005	0.003	0.001	0.001	0.000	0.001	0.001
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
CEO has MBA	0.127***	0.116***	0.280***	0.226**	0.200**	0.169*	-0.057	-0.072	0.113***	0.106***
	(0.036)	(0.036)	(0.103)	(0.105)	(0.083)	(0.087)	(0.063)	(0.068)	(0.040)	(0.041)
2-digit industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.369	0.374	0.474	0.486	0.320	0.339	0.122	0.124	0.157	0.158
N	859	859	859	859	859	859	859	859	859	859

Note: Robust standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level

Table 6. Regression of Other Performance Variables on Innovation Subsidy

	Dependent variables: Corporate performance				
	Sales/employment in log	TFP in log	Market share	Profit/sales	Loss dummy
	(1)	(2)	(3)	(4)	(5)
Innovation subsidy	0.147*	0.009	0.069	0.000	0.020
	(0.090)	(0.153)	(0.092)	(0.011)	(0.039)
SOE	0.386***	0.269	0.033	-0.018	0.065
	(0.136)	(0.211)	(0.129)	(0.020)	(0.066)
Political connection	0.228**	0.088	0.175**	0.011	-0.094***
	(0.089)	(0.142)	(0.083)	(0.009)	(0.035)
Firm's attributes					
Employment in log	-0.095***	0.322***	0.095***	0.006	-0.027**
	(0.030)	(0.049)	(0.030)	(0.004)	(0.012)
Firm age in log	0.138**	-0.127	-0.038	0.007	0.063***
	(0.064)	(0.100)	(0.060)	(0.008)	(0.023)
Export	0.176**	0.047	0.060	-0.009	-0.048
	(0.082)	(0.140)	(0.087)	(0.011)	(0.036)
R&D sales ratio	-2.488***	-1.422	1.434*	-0.065	0.963***
	(0.624)	(1.171)	(0.844)	(0.153)	(0.295)
Entrepreneur's attributes					
Years of schooling	0.084***	0.064***	0.022*	-0.000	0.016***
	(0.014)	(0.022)	(0.013)	(0.002)	(0.006)
Working experience	0.004	0.001	0.000	-0.000	0.003
	(0.004)	(0.006)	(0.004)	(0.000)	(0.002)
CEO has MBA	0.142*	0.011	-0.130	-0.007	-0.043
	(0.085)	(0.139)	(0.083)	(0.009)	(0.035)
2-digit industry	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes
R-Square	0.252	0.578	0.091	0.059	0.085
N	859	736	859	859	859

Note: Robust standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Appendix A: China Employer Employee Survey (CEES)

Table A1. Sample Size and Response Rates of CEES Survey in Hubei and Guangdong Provinces of China

	Number of observations	Response Rate (%)
Firms survey 2015 (Guangdong only)	573	82
Firms survey 2016	1,122	85
New sample (Hubei)	585	83
Follow up sample (Guangdong)	487	85
New sample (Guangdong)	50	--
Workers survey 2015 (Guangdong only)	4,838	88
Workers survey 2016	9,103	80
New sample (Hubei)	4,114	89
Follow up sample (Guangdong)	2,575	53
New sample (Guangdong)	2,414	94

Table A2. Two-Digit Industry of Manufacturing

Code	Industry (Chinese)	Industry (English)	# of obs.	%
13	农副食品加工业	Agricultural and By-Product Processing	61	5.13
14	食品制造业	Food Manufacturing	19	1.6
15	酒、饮料和精制茶制造业	Beverage Manufacturing	27	2.27
16	烟草制造业	Tobacco Product Manufacturing	3	0.25
17	纺织业	Textile	73	6.14
18	纺织服装、服饰业	Textile Product Manufacturing	82	6.9
19	皮革、毛皮、羽毛及其制品和制鞋业	Leather, Fur, Feather Product and Shoes Manufacturing	44	3.7
20	木材加工和木、竹、藤、棕、草制品业	Wood Processing, and Other Wood Product	12	1.01
21	家具制造业	Furniture Manufacturing	23	1.94
22	造纸和纸制品业	Paper Making and Paper Product Manufacturing	16	1.35
23	印刷和记录媒介复制业	Printing and Recording Media Reproducing	36	3.03
24	文教、工美、体育和娱乐用品制造业	Stationery, Athletic, Sporting, and Entertaining Goods	32	2.69
25	石油加工、炼焦和核燃料加工业	Petroleum processing, coking and nuclear fuel processing industry	2	0.17
26	化学原料和化学制品制造业	Chemical Materials and Product Manufacturing	31	2.61
27	医药制造业	Pharmaceutical	26	2.19
28	化学纤维制造业	Chemical Fiber Industry	2	0.17
29	橡胶和塑料制品业	Balata and Plastic Product Industry	45	3.79
30	非金属矿物制品业	Nonmetallic Minerals Product	114	9.6
31	黑色金属冶炼和压延加工业	Ferrous Metal Smelting and Rolling Processing	13	1.09
32	有色金属冶炼和压延加工业	Non-Ferrous Metal and Rolling Processing	21	1.77
33	金属制品业	Metal Product	80	6.73
34	通用设备制造业	General Machinery Manufacturing	35	2.95
35	专用设备制造业	Special Machinery Manufacturing	48	4.04
36	汽车制造业	Automobile Manufacturing	64	5.39
37	铁路、船舶、航空航天和其他运输设备制造业	Railway, Boat, Aviation, Aerospace and Other Transportation Equipment Manufacturing	8	0.67
38	电气机械和器材制造业	Electronic Machinery and Equipment	107	9.01
39	计算机、通信和其他电子设备制造业	Computer, communications and other electronic equipment manufacturing	131	11.03
40	仪器仪表制造业	Instruments Manufacturing	17	1.43
41	其他制造业	Other manufacturing	7	0.59
42	废弃资源综合利用业	Comprehensive utilization of waste resources	5	0.42
43	金属制品、机械和设备修理业	Metal products, machinery and equipment repair industry	4	0.34
	Total		1,188	100

Note: In regressions, 16 is merged into 15, 25 is merged into 26, 28 is merged into 29, 42 and 43 are merged into 41.

Appendix B: Some Additional Results

Table B1. Poisson Regression Models of Innovation Performance

	Dependent variables: Innovation performance					
	Total No. of patents in log		Total No. of invention patents in log		Total No. of foreign patents in log	
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation subsidy	0.807***	0.751***	0.348***	0.317***	0.108**	0.0954*
	(0.101)	(0.0994)	(0.0664)	(0.0662)	(0.0485)	(0.0509)
SOE		0.208		0.197**		-0.0233
		(0.139)		(0.0993)		(0.0659)
Political connection		0.305***		0.163**		0.0850
		(0.0979)		(0.0699)		(0.0575)
Firm's attributes						
Employment in log	0.216***	0.204***	0.146***	0.135***	0.0292*	0.0283**
	(0.0338)	(0.0326)	(0.0268)	(0.0263)	(0.0152)	(0.0142)
Firm age in log	0.0734	0.0508	0.0833*	0.0640	0.0165	0.0149
	(0.0754)	(0.0762)	(0.0483)	(0.0489)	(0.0477)	(0.0506)
Export	0.188*	0.209**	-0.0125	0.0144	0.128*	0.130*
	(0.101)	(0.1000)	(0.0714)	(0.0720)	(0.0675)	(0.0701)
R&D sales ratio	2.758***	2.881***	1.150**	1.262***	0.336**	0.366**
	(0.735)	(0.726)	(0.453)	(0.458)	(0.156)	(0.150)
Entrepreneur's attributes						
Years of schooling	0.0482***	0.0476***	0.0395***	0.0395***	0.0223**	0.0217**
	(0.0155)	(0.0156)	(0.0123)	(0.0123)	(0.00907)	(0.00848)
Working experience	0.00954**	0.00626	0.00435	0.00206	0.00132	0.000560
	(0.00450)	(0.00450)	(0.00308)	(0.00322)	(0.00209)	(0.00223)
CEO has MBA	0.304***	0.255***	0.200***	0.169***	-0.0139	-0.0192
	(0.0825)	(0.0827)	(0.0619)	(0.0652)	(0.0424)	(0.0465)
2-digit industry	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.288	0.293	0.293	0.300	0.353	0.360
N	859	859	859	859	859	859

Note: Robust standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table B2. OLS Regression Models with the Size X Subsidy Interaction Terms: Innovation Performance

	Dependent variables: Innovation performance				
	Patent dummy	Total NO. of patents in log	Total NO. of invention patents in log	Total NO. of foreign patents in log	New product dummy
	(1)	(2)	(3)	(4)	(5)
Innovation subsidy	0.331**	-1.305***	-1.853***	-1.142**	0.406***
	(0.136)	(0.500)	(0.502)	(0.453)	(0.156)
Firm size in log	0.031**	0.124***	0.043*	-0.009	0.035**
	(0.013)	(0.035)	(0.025)	(0.015)	(0.016)
Subsidy dummy × firm size in log	-0.008	0.408***	0.409***	0.224***	-0.040
	(0.022)	(0.092)	(0.092)	(0.083)	(0.027)
SOE	0.087	0.468**	0.505***	-0.063	0.002
	(0.057)	(0.190)	(0.175)	(0.124)	(0.067)
political connection	0.069**	0.326***	0.186**	0.095	0.043
	(0.034)	(0.106)	(0.086)	(0.065)	(0.041)
Firm's attributes					
Firm age in log	0.036	0.036	0.047	0.005	-0.008
	(0.024)	(0.063)	(0.043)	(0.032)	(0.027)
exporter	0.067*	0.201**	0.005	0.091*	0.096**
	(0.035)	(0.098)	(0.075)	(0.054)	(0.041)
R&D ratio	2.130***	7.376***	3.104***	1.671**	1.094**
	(0.583)	(1.595)	(1.164)	(0.728)	(0.552)
Entrepreneur's attributes					
Years of schooling	0.016***	0.041***	0.034***	0.024***	0.016***
	(0.005)	(0.014)	(0.012)	(0.009)	(0.006)
Working experience	0.001	0.006	0.002	0.000	0.001
	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)
CEO has MBA	0.116***	0.214**	0.157*	-0.078	0.107***
	(0.036)	(0.103)	(0.084)	(0.066)	(0.041)
2-digit industries	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes
R-Square	0.374	0.512	0.396	0.168	0.161
N	859	859	859	859	859

Note: Robust standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

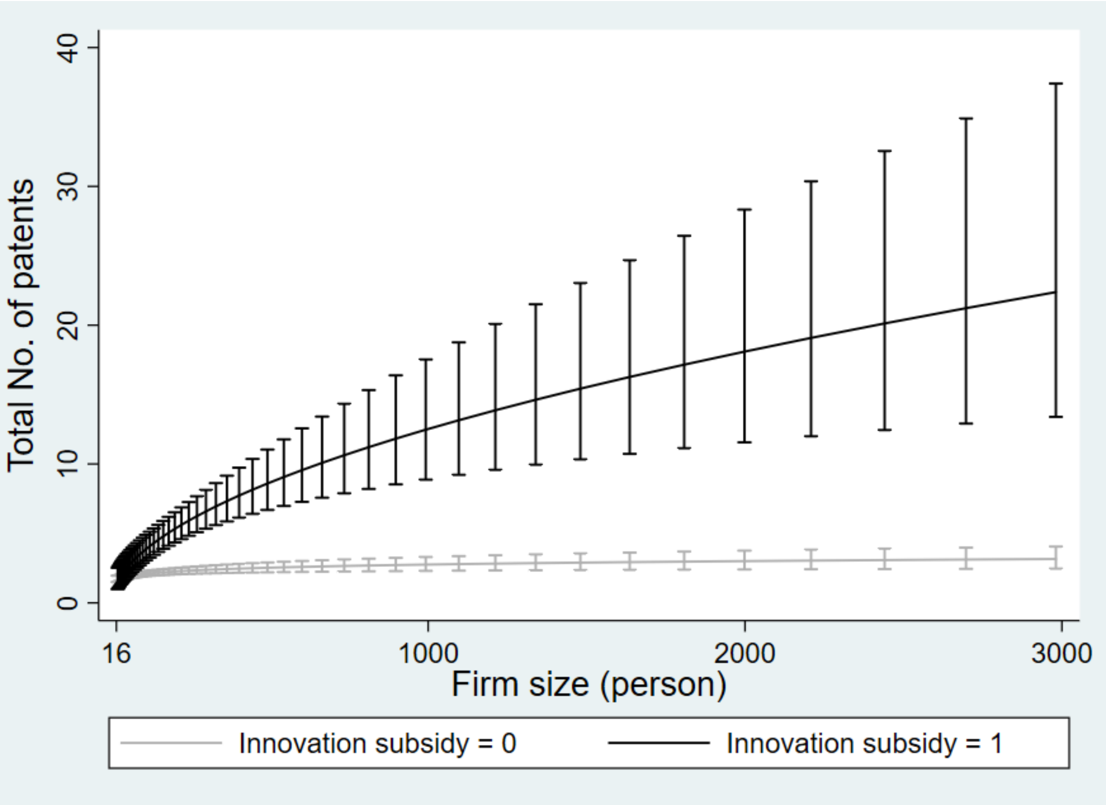
Table B3. OLS Regression Models with the Size X Subsidy Interaction Terms: Corporate Performance

	Dependent variables: Corporate performance				
	Sales/employment in log	TFP in log	Market share	Profit/sales	Loss dummy
	(1)	(2)	(3)	(4)	(5)
Innovation subsidy	-0.236	-0.761	0.882***	0.009	-0.134
	(0.323)	(0.557)	(0.340)	(0.036)	(0.120)
Firm size in log	-0.114***	0.284***	0.134***	0.006	-0.034**
	(0.034)	(0.057)	(0.033)	(0.004)	(0.013)
Subsidy dummy × firm size in log	0.068	0.136	-0.144**	-0.002	0.027
	(0.054)	(0.096)	(0.058)	(0.006)	(0.020)
SOE	0.374***	0.247	0.058	-0.018	0.060
	(0.135)	(0.214)	(0.130)	(0.021)	(0.067)
political connection	0.230**	0.089	0.171**	0.011	-0.094***
	(0.089)	(0.141)	(0.082)	(0.009)	(0.035)
Firm's attributes					
Firm age in log	0.137**	-0.132	-0.035	0.007	0.063***
	(0.064)	(0.100)	(0.060)	(0.008)	(0.023)
exporter	0.175**	0.038	0.063	-0.009	-0.048
	(0.082)	(0.140)	(0.087)	(0.011)	(0.035)
R&D ratio	-2.420***	-1.469	1.291	-0.067	0.990***
	(0.604)	(1.195)	(0.865)	(0.153)	(0.288)
Entrepreneur's attributes					
Years of schooling	0.086***	0.067***	0.019	-0.000	0.017***
	(0.014)	(0.022)	(0.013)	(0.002)	(0.006)
Working experience	0.004	0.002	-0.000	-0.000	0.003
	(0.004)	(0.006)	(0.004)	(0.000)	(0.002)
CEO has MBA	0.140*	0.008	-0.125	-0.007	-0.044
	(0.085)	(0.139)	(0.083)	(0.009)	(0.035)
R-Square	0.254	0.580	0.099	0.059	0.087
N	859	736	859	859	859

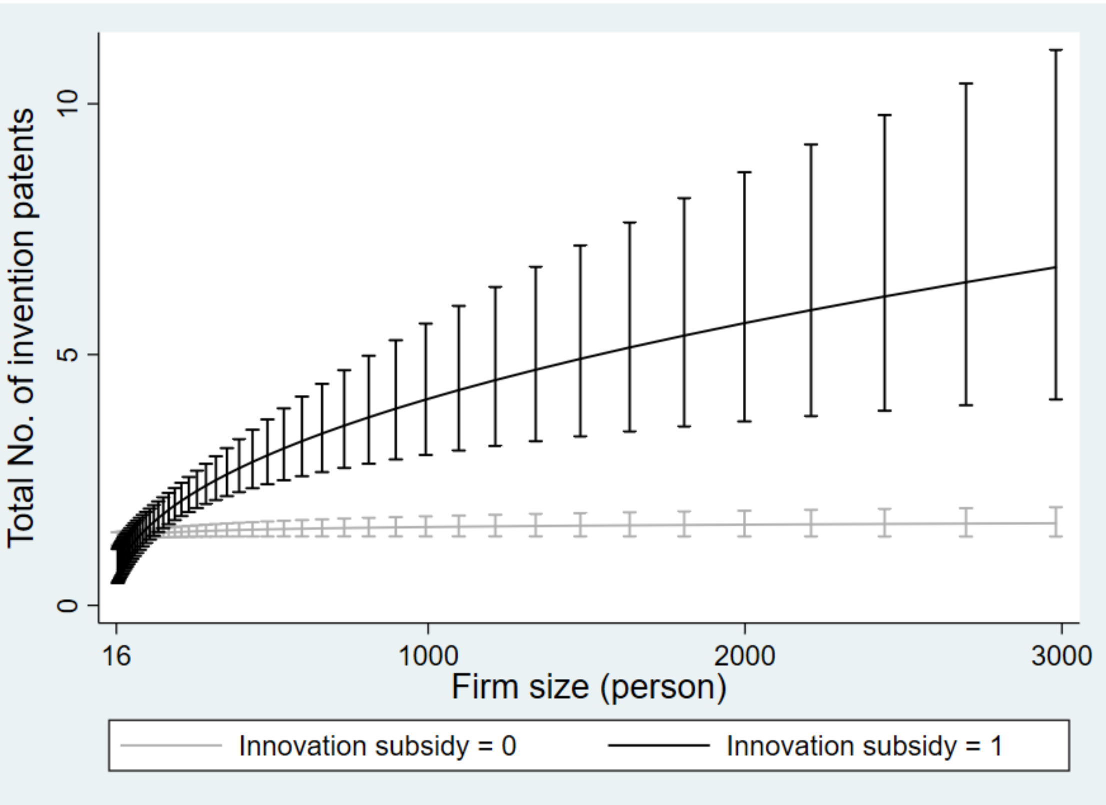
Note: Robust standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Figure B1. Innovation Outcomes as a Function of Firm Size (# of Employees)

Panel A: Total Number of Patents



Panel B: Total Number of Invention Patents



Panel C: Total Number of Foreign Patents

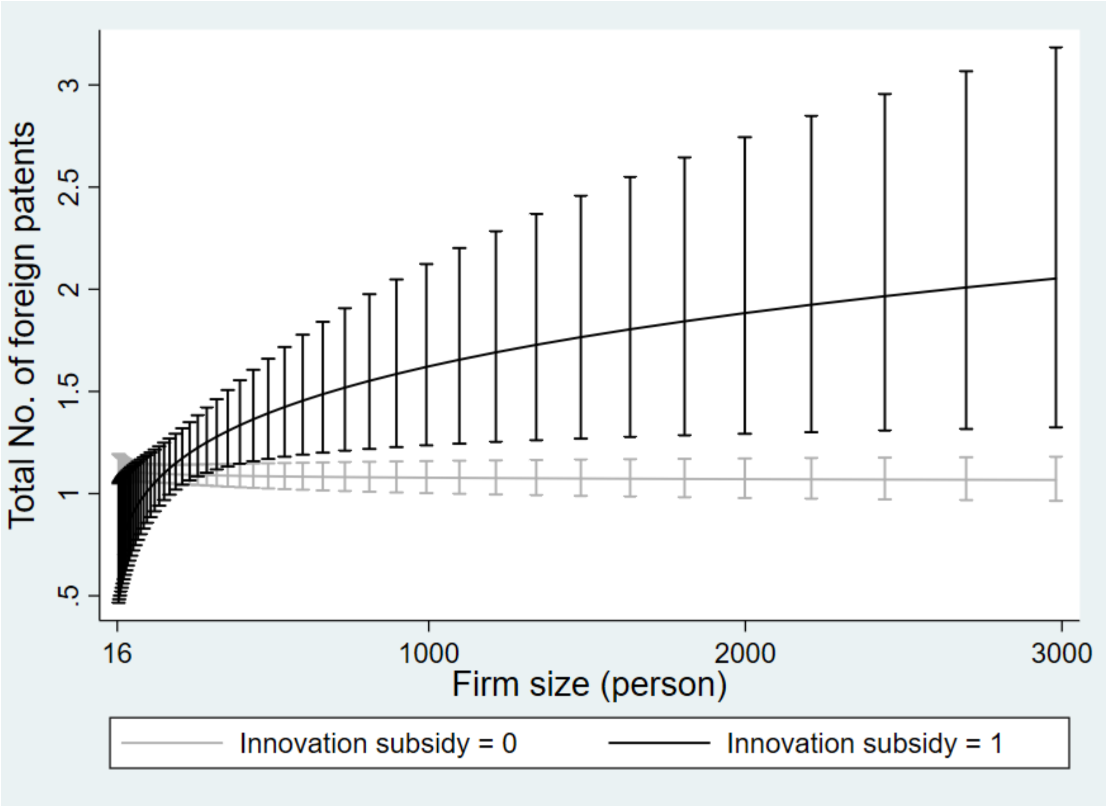
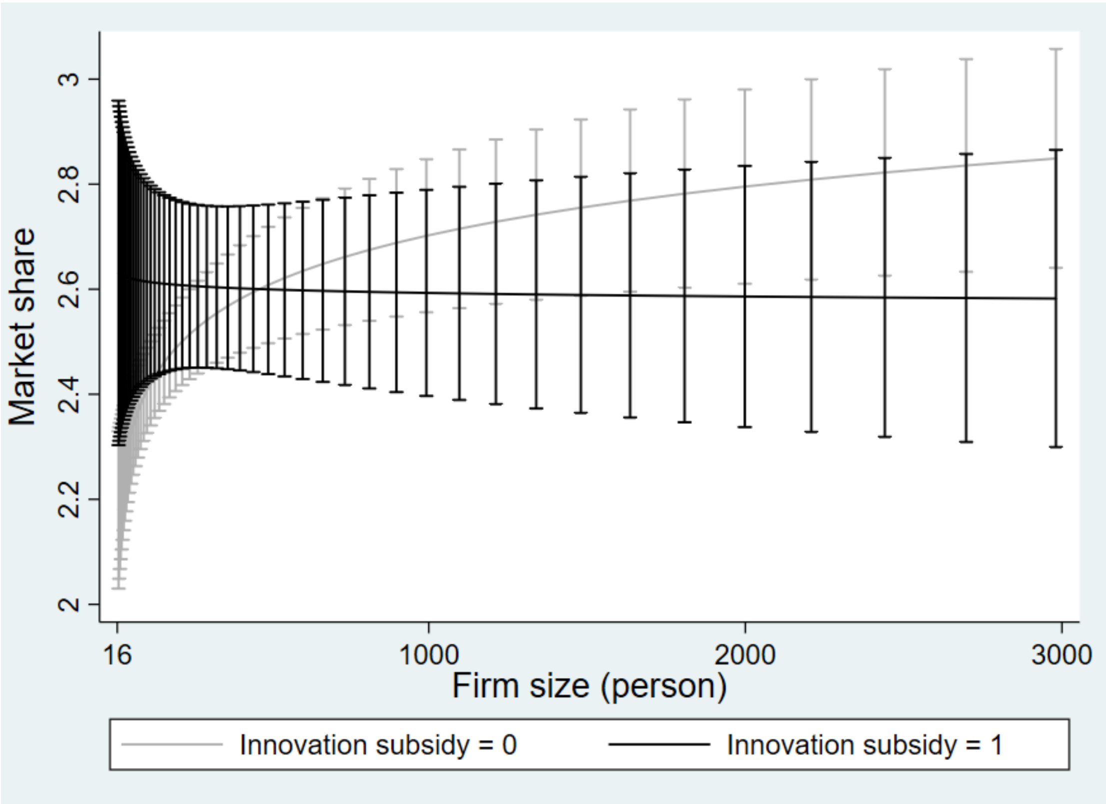


Figure B2: Market Share as a Function of Firm Size (# of Employees)



Appendix C: Propensity Score Matching Analysis

In this paper, we basically compare the firms that receive innovation subsidies to those that do not to assess the impacts of the government subsidies. If the subsidies were just assigned randomly to the firms, whether a firm actually receives the treatment (subsidy) or not would be independent of the outcome variable (innovation or performance) either when the subsidies are given or not. In this case, our procedure would be fine in estimating the average treatment effect.

In reality, however, the subsidized firms are not randomly selected. When granting subsidies, governments usually set some criteria that the firms that apply to subsidies must satisfy. At the same time, firms themselves make decision on whether to apply to the subsidies or not. Thus, the subsidized and non-subsidized companies in the sample are so different including the likelihood of coming up with innovation that they cannot be compared.

The propensity score matching developed by Rosenbaum and Rubin (1983) and others is one way to estimate treatment effects when the assignment of treatment is not random. This appendix applies the propensity score matching analysis to our estimation of the average treatment effect of innovation subsidies. Since we are especially interested in how the innovation subsidies affect the firms that actually receive the subsidies, we estimated the average treatment effect on treated (i.e., subsidized).

We start by finding the propensity score, which is the probability that a firm receive the subsidy, as a function of some observable characteristics. Here we follow the standard approach of estimating a logit model. The characteristics considered are political connection, state ownership, firm's employment in log, firm's age in log, export dummy, R&D sales ratio, entrepreneur's years of schooling, working experience, and a dummy indicates whether the CEO has MBA. We also included industry and province dummies.

The propensity score matching matches each firm that receives the innovation subsidy to the firms that do not receive the subsidy but have similar propensity scores. To find firms with "similar" propensity scores, we use K-nearest neighbor matching method. This approach matches each subsidized firm with K non-subsidized firms that have the closest propensity scores. For the value of K, we try 1, 2, 3, and 4.

Balancing test

We first conduct a balancing test to examine the quality of the matching. If the propensity score matching is successful, the distribution of the conditioning variables should be similar across the treatment group and the control group that is matched by propensity scores. As is shown in Table C1, for the entire sample, subsidized firms are significantly different from non-subsidized firms in all conditioning variables, including political connection, state ownership, firm's attributes and entrepreneur's attributes. When we apply 1-nearest matching, however, the differences disappear. Figure C1 graphically shows that the standardized percentages of the differences become smaller after matching.

Moreover, almost all observations in our sample are on the common support after the matching. As Table C2 reports, only 3.8% of non-subsidized firms and only 2.0% of subsidized firms are off the common support.

Estimation with matched data

Table C3-C7 presents the estimated mean differences in innovation performance between subsidized firms and non-subsidized firms in the matched subsamples. Table C3 shows estimation of the average treatment effect on treated (ATT) of innovation subsidy on the probability of having patents. The estimated effect is positive and statistically significant. The subsidized firms have 5%-7% higher probability of having patents.

Similarly, Table C4-C7 reports ATT on total number of patents, total number of invention patents, total number of foreign patents, and the new product dummy respectively. As Tables C4 and C5 shows, subsidized firms have 16%-24% more patents in total and 14%-21% more invention patents than non-subsidized firms on average.

For the number of foreign patents, the difference is much smaller (Table C6). The subsidized firms have only 11%-13% more foreign patents than non-subsidized firms. This difference is about 3-10 percentage point less than that when total number of invention patents is the outcome variable, and even less than half of that when total number of patents is the outcome variable.

For the new product dummy, the result of propensity score matching analysis is very different from the OLS result in the main part. The subsidized firms and non-subsidized firms are not significantly different in the likelihood of introducing new products when we used the matched data.

Table C8-C12 presents the estimated differences in productivity, market share, and profitability. Although the estimated ATT of innovation subsidy are all positive, none of them is statistically significant.

Overall, the results from the propensity score matching analysis are very similar to OLS regression results reported in the main part of the paper. The innovation subsidies encourage only incremental innovations rather than radical innovations, and do not seem to help firms to increase productivity, market share, or profitability. For the introduction of new products, the propensity score matching gives a different result than the OLS regression. For matched sample, the subsidized firms and non-subsidized firms are not different in the likelihood of introducing new products.

Table C1. Standardized Percentage Bias of Covariates Between Treated and Control Group

	Before match				After match			
	Treated Mean (N=196)	Control Mean (N=663)	% bias	T-stat	Treated Mean (N=192)	Control Mean (N=638)	% bias	T-stat
Political Connection	0.35	0.21	32.10	4.13***	0.35	0.33	4.70	0.43
SOE	0.12	0.05	27.40	3.83***	0.13	0.13	-1.90	-0.15
Firm's attributes								
Employment in log	5.97	4.77	81.10	10.22***	5.95	6.01	-4.00	-0.37
Firm age in log	2.55	2.24	51.80	6.00***	2.54	2.53	1.60	0.16
Export	0.56	0.34	43.90	5.47***	0.56	0.54	4.30	0.41
R&D sales ratio	0.04	0.01	48.00	7.76***	0.03	0.04	-8.60	-0.83
Entrepreneur's attributes								
Years of schooling	15.52	13.78	59.40	7.17***	15.52	15.47	1.60	0.16
Working experience	22.74	20.10	26.30	3.22***	22.83	22.45	3.80	0.37
CEO has MBA	0.45	0.24	46.10	5.94***	0.45	0.41	9.00	0.82

Note: The standardized % bias is the % difference of the sample means in the treated and control sub-samples as a percentage of the square root of the average of the sample variances in the treated and control groups (Rosenbaum and Rubin, 1985). The method of matching is the 1-nearst neighbor matching. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table C2. Treatment Assignment of Propensity Matching

	Off support		On support		Total	
	No.	Row %	No.	Row %	No.	Row %
Untreated (non-subsidized)	25	3.8	638	96.2	663	100
Treated (subsidized)	4	2.0	192	98.0	196	100

Note: The method of matching is the 1-nearst neighbor matching.

Figure C1. Standardized Percentage Bias Across Covariates

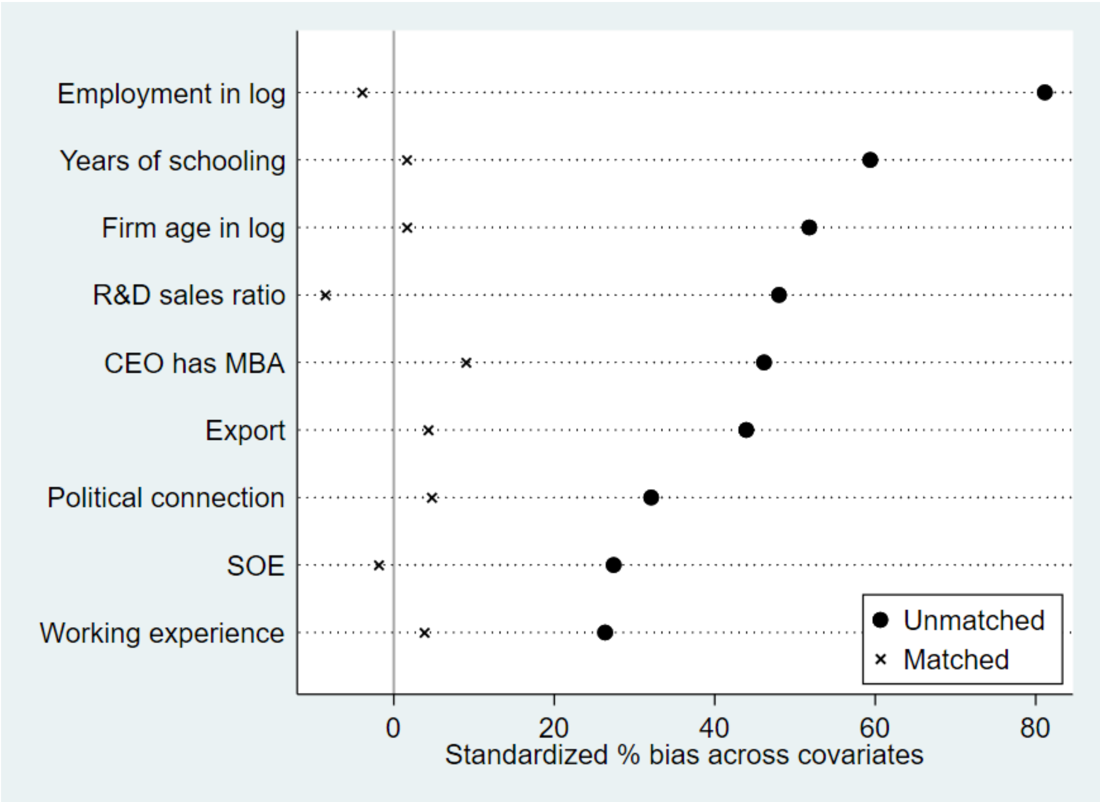


Table C3. Average Treatment Effect of Technological Innovation Subsidy

	Outcome: Patent dummy			
	Treated (N=192)	Control (N=638)	Mean Difference	S.E.
Unmatched	0.79	0.27	0.52	0.04***
Matched				
ATT (k=1)	0.79	0.51	0.28	0.07***
ATT (k=2)	0.79	0.52	0.27	0.07***
ATT (k=3)	0.79	0.51	0.27	0.07***
ATT (k=4)	0.79	0.51	0.28	0.05***

Note: K-nearest neighbor matching method is used when matching. Bootstrapped standard errors are estimated for matched sample. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table C4. Average Treatment Effect of Technological Innovation Subsidy

	Outcome: Total No. of patents in log			
	Treated (N=192)	Control (N=638)	Mean Difference	S.E.
Unmatched	2.52	0.61	1.91	0.11***
Matched				
ATT (k=1)	2.49	1.54	0.94	0.23***
ATT (k=2)	2.49	1.50	0.99	0.24***
ATT (k=3)	2.49	1.44	1.04	0.16***
ATT (k=4)	2.49	1.44	1.05	0.19***

Note: K-nearest neighbor matching method is used when matching. Bootstrapped standard errors are estimated for matched sample. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table C5. Average Treatment Effect of Technological Innovation Subsidy

	Outcome: Total No. of invention patents in log			
	Treated (N=192)	Control (N=638)	Mean Difference	S.E.
Unmatched	1.27	0.27	0.99	0.08***
Matched				
ATT (k=1)	1.25	0.85	0.40	0.21*
ATT (k=2)	1.25	0.87	0.38	0.19**
ATT (k=3)	1.25	0.82	0.43	0.14***
ATT (k=4)	1.25	0.80	0.45	0.15***

Note: K-nearest neighbor matching method is used when matching. Bootstrapped standard errors are estimated for matched sample. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table C6. Average Treatment Effect of Technological Innovation Subsidy

	Outcome: Total No. of foreign patents in log			
	Treated (N=192)	Control (N=638)	Mean Difference	S.E.
Unmatched	0.39	0.06	0.33	0.05***
Matched				
ATT (k=1)	0.37	0.15	0.22	0.11**
ATT (k=2)	0.37	0.16	0.21	0.13*
ATT (k=3)	0.37	0.12	0.25	0.11**
ATT (k=4)	0.37	0.12	0.25	0.10**

Note: K-nearest neighbor matching method is used when matching. Bootstrapped standard errors are estimated for matched sample. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table C7. Average Treatment Effect of Technological Innovation Subsidy

	Outcome: New product dummy			
	Treated (N=192)	Control (N=638)	Mean Difference	S.E.
Unmatched	0.66	0.34	0.32	0.04***
Matched				
ATT (k=1)	0.66	0.42	0.24	0.08
ATT (k=2)	0.66	0.45	0.21	0.08
ATT (k=3)	0.66	0.47	0.19	0.06
ATT (k=4)	0.66	0.47	0.19	0.06

Note: K-nearest neighbor matching method is used when matching. Bootstrapped standard errors are estimated for matched sample. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table C8. Average Treatment Effect of Technological Innovation Subsidy

	Outcome: Sales/employment in log			
	Treated (N=192)	Control (N=638)	Mean Difference	S.E.
Unmatched	3.83	3.48	0.36	0.09***
Matched				
ATT (k=1)	3.85	3.61	0.23	0.16
ATT (k=2)	3.85	3.68	0.17	0.16
ATT (k=3)	3.85	3.67	0.18	0.16
ATT (k=4)	3.85	3.69	0.16	0.13

Note: K-nearest neighbor matching method is used when matching. Bootstrapped standard errors are estimated for matched sample. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table C9. Average Treatment Effect of Technological Innovation Subsidy

	Outcome: TFP in log			
	Treated (N=192)	Control (N=638)	Mean Difference	S.E.
Unmatched	3.54	2.74	0.80	0.20***
Matched				
ATT (k=1)	3.48	3.58	-0.09	0.40
ATT (k=2)	3.48	3.52	-0.04	0.31
ATT (k=3)	3.48	3.46	0.02	0.32
ATT (k=4)	3.48	3.55	-0.06	0.30

Note: K-nearest neighbor matching method is used when matching. Bootstrapped standard errors are estimated for matched sample. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table C10. Average Treatment Effect of Technological Innovation Subsidy

	Outcome: Market share			
	Treated (N=192)	Control (N=638)	Mean Difference	S.E.
Unmatched	2.68	2.39	0.28	0.08***
Matched				
ATT (k=1)	2.68	2.80	-0.12	0.11
ATT (k=2)	2.68	2.76	-0.08	0.13
ATT (k=3)	2.68	2.72	-0.04	0.11
ATT (k=4)	2.68	2.70	-0.02	0.13

Note: K-nearest neighbor matching method is used when matching. Bootstrapped standard errors are estimated for matched sample. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table C11. Average Treatment Effect of Technological Innovation Subsidy

	Outcome: Profit/sales			
	Treated (N=192)	Control (N=638)	Mean Difference	S.E.
Unmatched	0.05	0.04	0.01	0.01
Matched				
ATT (k=1)	0.05	0.04	0.01	0.02
ATT (k=2)	0.05	0.04	0.01	0.02
ATT (k=3)	0.05	0.04	0.00	0.02
ATT (k=4)	0.05	0.05	0.00	0.02

Note: K-nearest neighbor matching method is used when matching. Bootstrapped standard errors are estimated for matched sample. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table C12. Average Treatment Effect of Technological Innovation Subsidy

	Outcome: Loss dummy			
	Treated (N=192)	Control (N=638)	Mean Difference	S.E.
Unmatched	0.16	0.18	-0.02	0.03
Matched				
ATT (k=1)	0.16	0.15	0.02	0.05
ATT (k=2)	0.16	0.15	0.02	0.05
ATT (k=3)	0.16	0.14	0.03	0.05
ATT (k=4)	0.16	0.13	0.03	0.05

Note: K-nearest neighbor matching method is used when matching. Bootstrapped standard errors are estimated for matched sample. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.