Government-subsidized R&D and Firm Innovation:

Evidence from China *

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Abstract

This study investigates the effects of government R&D programs on firm innovation outputs, which are measured by the number of patents, sales from new products, and exports. Particularly, we examine the effects of Innovation Fund for Small and Medium Technology-based Firms (Innofund), which is one of the largest government R&D programs that support R&D activities of small and medium-sized enterprises in China. Using a panel dataset on Chinese manufacturing firms from 1998 to 2007, we find that Innofund-backed firms generate significantly higher technological and commercialized innovation outputs compared with their non-Innofund-backed counterparts and the same firms before winning the grant. Moreover, the changes in the governance of Innofund in 2005 from a centralized to a decentralized one because of policy amendments have significant effects on the effectiveness of the program. Specifically, the magnified effects of Innofund on technological innovation outputs become significantly stronger after the governance of Innofund becomes more decentralized. Identification problems are addressed by utilizing both propensity score matching and two-stage estimation approaches.

Keywords: government R&D Program, governance, innovation, China

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1. Introduction

Government funding for corporate research and development (R&D) is a major practice in most countries. The major rationale for such government initiative is that firms may underinvest in R&D under a free market because of the externalities generated by these activities (Nelson, 1959; Arrow, 1962), as well as the information issues associated with these projects (Greenwald et al., 1984; Hall and Lerner, 2009). Hence, government engagement is raised as a mechanism to respond to market failures (Romer, 1986; Aghion and Howitt, 1990). Underinvestment in R&D has been well reasoned theoretically and is evident empirically. However, determining the extent to which government intervention could stimulate firms to invest more in R&D and consequently improve their economic and technological performance is a challenging empirical question.

Empirical findings on the effects of government R&D programs are inconclusive. Griliches and Regev (1998) and Branstetter and Sakakibara (1998) find that government-subsidized firms achieve higher productivity and profitability in Israel and Japan, respectively. Moreover, such firms grow faster (Lerner, 2000), access other external finances more successfully (Lerner, 2000; Aschhoff, 2009), invest more in R&D activities (Audretsch et al., 2002; Lach, 2002; Görg and Strobl, 2007; Aerts and Schmidt, 2008; Czarnitzki and Lopes-Bento, 2013), and generate higher social returns than their counterparts do (Griliches and Regev, 1998; Irwin and Klenow, 1996). Nevertheless, a considerable number of studies also indicate that public R&D programs have not stimulated firm performance (Klette and Møen, 1999; Brander et al., 2008) or have limited positive effects on corporate R&D spending, except for small firms (Lööf and Hesmati, 2005) or research-oriented projects

(Clausen, 2009). Several studies even find that government R&D subsidies crowd out private R&D inputs (crowding out effect), thereby consequently reducing social welfare and growth (David, et al., 2000; Wallsten, 2000; Acemoglu et al., 2013).

The mixed findings on the effects of government R&D programs have several implications. First, institutions may influence the effects of such R&D programs. Public R&D finance is introduced as a solution to the underinvestment in R&D activities by profit-driven businesses. Institutions affect the degree of the role of the market in allocating resources and the efficiency of the government (Acemoglu et al., 2005). As a result, the institutions under which the market interacts with government initiatives are ultimately important to determine the success of the government R&D initiatives. Indeed, empirical studies find that the effects of public R&D subsidies across countries exhibit significant heterogeneity (Guellec and van Pottelsberghe, 2000; Cincera et al., 2009). Moreover, a few works based on U.S. data demonstrate a crowding-out effect of public R&D programs (e.g., Wallsten, 2000; Acemoglu et al., 2013), whereas most studies based on data from non-U.S. countries find universally positive effects of such programs despite the variation in the degree of complementary influence (e.g., Lach, 2002; Cincera et al., 2009; Czarnitzki and Lopes-Bento, 2013). Second, even under similar institutions, the governance of these public R&D programs may result in variations on the incentives provided to government agencies who allocate the resources. Government agencies play an essential role in allocating resources through public R&D programs. Thus, the governance of these programs will expectedly affect their effectiveness. However, to our knowledge, focus on the governance of government R&D programs and its effects is insufficient. Third, endogeneity issues in empirical examinations resulting from data constraints are also

a major challenge in existing studies, which may have also contributed to the conflicting findings (Klette et al., 2000).

This study attempts to fill some of the abovementioned gaps. We examine the effects of Innovation Fund for Small and Medium Technology-based Firms (Innofund) on the innovation outputs of firms. Innofund is the largest government program that aims to support corporate R&D activities of small- and medium-sized enterprises (SMEs) in China. Specifically, we address two major questions. First, we examine whether Innofund enables firms to generate more outputs on both commercialized innovation (measured by sales from new products and exports) and technological innovation (measured by patent counts). Second, we estimate whether the changes in Innofund governance brought about by the exogenous policy shock in 2005 influence the effects of Innofund.

Using a panel dataset on Chinese manufacturing firms from 1998 to 2007, we find that Innofund-backed firms generate significantly higher innovation outputs (both commercial and technological innovation outputs) than their non-Innofund-supported counterparts and themselves before gaining Innofund support. We also observe stronger magnified effects of Innofund on technological innovation outputs (measured by the count of newly granted patents) after 2005 when Innofund governance shifted from a centralized screening system to a more decentralized one. Our results imply that decentralized governance is more effective than the centralized one in public R&D investments.

The major challenge with estimations on public R&D programs is the identification issues that result from selection biases and omitted variables. We

attempt to address these identification concerns by using two approaches, i.e., propensity score matching (PSM) and two-stage estimations with instrumental variables (IVs). We use the PSM approach to match Innofund-backed firms with non-Innofund-backed firms on the basis of various criteria that may predict the probability of a firm being selected by Innofund and the future innovation potentials of the firm. Subsequently, we employ two-stage estimations with two IVs to further address endogeneity issues. The first IV refers to the total number of firms located in high-tech zones in a given city for a given year. The second IV refers to the ratio of annual investments in fixed assets made by local governments over GDP at the county level for a given year. Both IVs reflect how ambitious the local governments are. We suggest that the more ambitious the local governments are, the more likely they support local firms to participate in Innofund program competition and also exert more effort to lobby the upper-level governments for local firms to win Innofund grants. Statistically, the two-stage estimations confirm the relevance and the exogeneity of the IVs, thereby indicating that the two IVs are qualified. Our major findings remain robust after the identification issues are addressed.

Our study differs from and complements the existing literature in three aspects. First, our study is the first one that links the governance of the government R&D programs and the effects of such programs. The Innofund program, which was initiated by the central government in 1999, underwent a significant change in its governance in 2005 when the central government decided to shift from a centralized project screening system into a relatively decentralized one. This exogenous policy change provides us with the opportunity to scrutinize the use of the quasi-experiment approach and determine how governance of public R&D programs influences the

effects of such programs. Our study proves that the governance of government R&D programs is an important factor that contributes to the effects of such programs. Second, this study is among the first examinations on the effects of government R&D programs in China. The Chinese government has been deeply involved in businesses, particularly in resource allocation. The inefficiencies that result from the involvement of the Chinese government in business are well documented (Brandt et al., 2013; Guo et al., 2014). Thus, China serves as an interesting case to examine whether government R&D support is effective in an economy where "government failures" are rampant and the market remains immature. Third, we employ two approaches to address the identification concerns in this study. Most existing studies on government R&D programs mainly employ PSM approach to mitigate selection biases. In our study, we not only employ PSM but also apply two-stage estimations to control the potential concerns with missing variables. Hence, we attempt to shed some light on the existing discussions with regard to why empirical findings are inconclusive in terms of the effects of government R&D programs.

The rest of this paper is organized as follows: Section 2 introduces the institutional background of the Innofund program and the policy changes it underwent in 2005. Section 3 describes the sample and data. Section 4 presents the empirical findings on whether Innofund affects innovation outputs of firms and examines the robustness of the results. Section 5 reports the findings on the effects of the policy change of Innofund governance. Section 6 provides the conclusions.

2. Institutional Background of the Innofund Program

2.1 Introduction of Innofund Program

Innofund Program is a special government R&D program established upon the

approval of the State Council in May 1999. Innofund aims to *facilitate and encourage the innovation activities of small and medium technology-based enterprises (SMTEs) and commercialization of research by way of financing, trying to bring along and attract outside financing for corporate R&D investment of SMTEs*." At the same time, as a nonprofit-making government policy, "it is oriented towards social welfare induced by positive effect of innovation."[1]

The principal criteria for applying to Innofund are as follows: The project should comply with national industrial technology policies, exhibit relatively high potential for economic and social benefits, and competitive in the market. The applicant should be a business corporation with generally not more than 500 employees, not less than 30% of which should have received higher education. The annual R&D investment of the firm should be at least more than 3% of the total sales, and the number of R&D employees should be more than 10% of the total number of employees. Firms with leading products in the market with an economy of scale production must also exhibit good economic performance. The following projects are prioritized: projects with advanced technology or independent intellectual property rights and high value added; projects established by researchers or overseas returnees to commercialize their scientific achievements; innovation projects jointly initiated by firms, universities, and research institutions; and projects that utilize new and advanced technologies to revive the stock assets of traditional industries and drive job creation.

Innofund provides three forms of financing, namely, appropriation, interest-free bank loans, and equity investment. Appropriation is provided as start-up capital

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[1] Source: http://www.innofund.gov.cn/

for small firms founded by a researcher with scientific achievements. Partial subsidies are also provided to SMEs for the development of new products and pilot production. The total amount of subsidies for an individual project is generally between 1–2 million RMB. Firms are required to provide dollar-to-dollar matching investments in the funded projects. Interest-free loans are provided mainly to SMEs that require external financing from commercial banks to expand the production of innovative projects. Generally, equity investment is reserved for projects that use advanced technology, have high innovation capacity, and have market potential in emerging industries. On average, Innofund support should not exceed 20% of the registered capital of the investee firm.

From 1999 to 2011, Innofund provided more than 19.17 billion RMB to 30,537 projects, 27,498 (86%) of which were supported through appropriation, 2,880 through interest-free loans, and 1,159 through other forms, including bank loan insurance, equity investment, and other forms of subsidies. The size of direct investments by Innofund appears to be modest compared with the total expenditure for government R&D in China. However, according to official reports, Innofund has induced 1:11 external financing from local governments, banks, and venture capitalists. Innofund has also incubated several innovative projects of world-class high-tech firms, such as Zhongxingwei and Huawei. Since 1999, the program has created approximately 450,000 new jobs and generated 209.2 billion RMB in sales, 22.5 billion RMB in tax income, and 3.4 billion RMB in exports. By the end of 2008, 82 out of 273 publicly listed companies in China's SME Stock Exchange were once supported by Innofund.[2]

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[2] http://www.innofund.gov.cn/.

2.2   **Innofund Governance Before and After 2005**

The governance of Innofund Program underwent a systematic change in 2005. In general, two levels of government agencies are involved in the management of Innofund. At the central level, the Innofund Administration Center (IAC) under the Ministry of Science and Technology (MOST) is in charge of Innofund operations, including the issuance of the application guide, preparation of proposals for the preferred fields and industries to support for each year,[3] screening and evaluation of projects ex-ante, signing of contracts with firms, and conducting post-investment project assessments. The Ministry of Finance (MOF) plays a regulatory role and approves the application guidelines and yearly budget, transfers funds to the IAC twice a year, and assesses IAC operation. The MOST and MOF report yearly to the State Council on the operation and performance of Innofund. The IAC must adhere to the principles of honest application, fair processing, strict selection, and transparent administration. According to IAC reports, fraudulent cases for each year constituted less than 0.5% of the total projects for the past 10 years.

At the local level, each province has an Innofund office under the Provincial Science and Technology Committee, which reports to the IAC. The role of the local Innofund office was transformed substantially in 2005 when the Innofund administration was reformed. The policy changes simplified the application processes, decentralized the screening and evaluation of projects, and delegated more power to local Innofund offices in project selection.

Before 2005, the Innofund administration was hierarchical and centralized. Local Innofund offices principally acted as bridges between IAC, and the local firms

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[3] A consulting committee composed of technology and management specialists, economists, and entrepreneurs help identify preferred areas to support and provide advice on Innofund guidelines.

had no considerable involvement in project selection. The local Innofund offices had three major responsibilities. These offices delivered and promoted IAC guidelines and policies to local firms or agencies to guide them in preparing the required application documents. The local offices also collected the application documents and certified the qualifications of applicants. Finally, the local offices recommended and forwarded the application documents of qualified projects to the IAC. Subsequently, a panel of experts at the IAC evaluated the submitted applications and promulgated the final funding decisions. Local Innofund offices were only recommendatory bodies that did not contribute in the final decisions of the awardees. No resources were to be allocated by the local governments to the recommended projects until the IAC announced its final decision. After the IAC reached a decision, the provincial Bureau of Finance was normally required to match 50% of the total support from the central government to IAC-sponsored projects.

In 2005, the operations and governance of Innofund were reformed, and a new application and screening system was introduced. The system considerably increased the transparency of project screening and decentralized decision making in project selection. The role of local Innofund offices was substantially shifted. Local governments at the provincial level were now required to set up their own Innofund programs and take responsibility for the initial project selection. In particular, project assessments by local Innofund offices constitute 30% of the final decision of the IAC. Moreover, in contrast to previous practice, local Innofund offices are required to commit at least 50% of the proposed support (25% for provinces in Western China) to selected local projects before even recommending the projects to the IAC. The list of projects that local offices plan to recommend must be published in their websites for

two weeks before the applications are submitted to IAC. Accordingly, these offices must respond to public criticisms on their proposed projects.

The policy change in 2005 fundamentally changed the ex-ante project screening of the Innofund Program. The major feature of this policy change is the delegation of power on project selection to local Innofund offices. Compared with the hierarchical decision making process, the decentralization of decision making may reduce inefficiencies that result from the hierarchical decision making process by solving information issues and considering that local officers have more knowledge on local firms. Thus, information issues can be addressed immediately. The delegation of decision making power and the newly introduced co-investment mechanism also aligned with the interests of local and central governments, and provided more incentives to local Innofund offices in terms of project screening and monitoring. Indeed, anecdotes reveal that the reforms introduced in 2005 ushered in creative operations of local Innofund offices. For example, Zhejiang province further delegated decision making powers on project screening to lower administrative levels, such as city or county governments. In Chongqing and Hunan provinces, the local Innofund offices cooperated with other government and consulting agencies, such as the local industrial and commercial bureau, tax bureau, law firms, and accounting and auditing firms, to collect information on candidate firms for project selection. These efforts are also reflected in the total amount of funds granted by the local Innofund offices. According to the official report of the Innofund program in 2005, local governments recommended a total of 4,207 projects, and the amount of funds committed by local government was more than 1.2 billion RMB or approximately six times that used by the local government to provide matching funds before 2005. We

expect this systematic change in the governance of Innofund to influence the effects of the program.

3. Data and Sample

3.1 Variables and Data Sources

We are interested in the changes in innovation outputs, particularly on commercialized and technological innovation outputs of the firms after they receive support from Innofund. Commercialized innovation outputs are measured by annual sales from new products and exports of a firm, whereas technological innovation outputs are measured by the number of newly granted patents of a firm for each year. We also control several firm-specific variables including age, size, leverage ratio, and ownership structure of firms (detailed definitions of the variables can be found in Table A-1).

Our data are acquired mainly from three sources. Basic information on Innofund-backed firms is obtained from the Innofund Program website (http://www.innofund.gov.cn). The names of Innofund-awarded firms have been publicly announced on the website each year since 1999. The website provides the names and addresses of the firms, the nature of the projects, the date the firm was granted Innofund support, the type of support from Innofund, and the results of performance evaluation of the project (i.e., terminated during the process or finished on time and achieved the proposed goal). Firm-level data on financial information, sales from new products, exports, and other firm-specific characteristics are obtained from the Above-scale Industrial Firms Panel 1998-2007 (ASIFP). ASIFP is composed of all state- and non-state-owned industrial firms with annual sales of at least

5 million RMB (US$750,000) between 1998 and 2007. This database provides sophisticated financial data and other firm-specific information, including location, industry, age, and ownership structure. Patent data are obtained from the State Intellectual Property Office (SIPO) patent database. The SIPO database provides complete information on all patents granted in China, including the application and publication number of the patent, application and grant year, IPC classification number, type of the patent, and assignee of the patent.

3.2 Data Matching

The first challenge in this study is data matching because the names of the firms listed in the three databases may not be fully consistent. First, we need to match the list of Innofund-backed firms in the Innofund website with the list in the ASIFP database to identify which firms in the ASIFP database have won Innofund support and obtain detailed financial information for these firms. We employ both computerized matching and manual matching approaches to match the two databases. As mentioned, both the Innofund website and ASIFP provide information for the names, locations (at city level), and industries of the firms by year. ASIFP also provides information for the legal person code of all the firms in the database. We use these information to conduct the matching.

First, we apply a three-stage matching strategy for the computerized matching, which is similar to that used by the NBER Patent Data Project[4], to ensure accuracy of the matching. In the first step, we standardize the firm names in the two databases to prepare for the matching. Under the Company Law of China, a company name must

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[4] https://sites.google.com/site/patentdataproject/Home.

contain four elements, namely, a trade name, industry sector, legal entity identifier (e.g., Limited Liability Company or Joint Stock Limited Liability Company), and the administrative region. We first create a "standard name" for a firm by removing the punctuations, spaces, or other special characters (e.g., !, @, #, $, %, ^, &, *, -, =, [, /,], \, etc.)[5] and standardizing the legal entity identifiers (e.g., we converted Limited into Ltd.). This step is carried out to prevent the matching quality from being affected by inconsistencies in the formats of firm names listed in the two databases. Moreover, we created a "stem name" for each firm by removing the administrative region and legal entity identifiers in the firm name (e.g., a firm called "Beijing Tian Fa Logistics Ltd" is changed to "Tian Fa Logistics"). This step is carried out to prevent the matching quality from being affected by the mistake driven by input errors with legal entity identifiers or administrative regions of firms.

In the second stage, we identify Innofund-backed firms from ASIFP by conducting matching with "standard names", "stem names", and other information in the two databases by Innofund awarding year. We first accurately match the two databases using the "standard names", locations (at city level), and standard industry codes (SICs) of firms for the year when Innofund-backed firms won the grant. If a firm was awarded an Innofund grant in 2000, then we use the aforementioned matching information of the firm listed in the Innofund website of the said year to match with that of the firms listed in ASIFP of the same year. We generate a matched file called "full marching_2000" for the matching results of 2000. Year and location are ultimately important in matching. According to the Company Law of China, a company has an exclusive right to its name on a regional basis. A company name

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[5] These characters may be input into the names of the databases by mistakes.

must be unique and identical within its region. Thus, if a firm has exact the same Chinese name and location in the two databases for the same year, then it should be the same firm. We repeat this procedure for each Innofund awarding year and the counterpart year of ASIFP, and generate the matching files by year accordingly.

Next, we repeat the previously mentioned matching procedures by replacing the "standard names" with the "stem names" and generate a matched file called "partial matching" for each Innofund awarding year. We use "stem names" to conduct additional matching to determine potential missed cases during matching using "standard names" (we may not have exhausted all the expressions of the legal entity identifiers and converted them into standard identifiers when we created "standard names"). Finally, we combine the matching results of the "full matching" and "partial matching" by year and delete duplicates using the legal person codes of each firm by year. After these matching procedures, we generate a cross-sectional dataset for each year between 1998 and 2007 in which Innofund-backed firms are identified in ASIFP for the year when they obtained the grant.

After the computerized matching, we conduct manual matching. We manually check all Innofund-backed manufacturing firms that are not matched by computerized matching using online search engines such as Google and Baidu. We mainly focus on checking the names, business nature, legal person codes, and Innofund granting records of the firms to ensure that we do not miss some observations because of slight variations of the trade names of firms listed in the two databases. Similarly, after the manual matching, we establish a cross-sectional dataset for each year in which Innofund-backed firms that are missed in computerized matching are identified in ASIFP for the year they obtained the grant.

Finally, we merge all identified Innofund-backed firms into ASIFP. We first combine the yearly matching results from the computerized and manual matching by year and create a pooled cross-sectional dataset entitled "final matching" for each year in which all Innofund-backed firms are identified from ASIFP for the year they won the grant. We thereby obtain the legal person codes of all identified Innofund-backed firms and distinguish the time when the firm was awarded an Innofund grant. Finally, 2,638 firms that won backing from Innofund at least once between 1999 and 2007 are identified for the estimations.[6] We build the panel data for the identified firms by merging the firms listed in "final matching" into ASIFP by year and adding two dummy variables into ASIFP to distinguish whether the firm won and when it won Innofund (Brandt et al., 2012). The final sample consists of 18,224 firm-year observations for Innofund-backed firms.

With this matching strategy, we ensure that the variations or the changes of firm names over the years will not affect the quality of our matching. First of all, by controlling the "standard names", locations (at city level), industries of firms, and the year in computerized matching, we may ensure that type I error does not occur in matching. According to the Company Law of China, a company name must contain four elements, namely, a trade name, industry sector, legal entity identifier (e.g., Limited Liability Company or Joint Stock Limited Liability Company), and the

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[6] The number of Innofund-backed firms for the estimations dropped substantially from 11,977 (the number of project backed between 1999 and 2007) to 2,638 for estimations during the examination period because of several reasons. The ASIFP database covers manufacturing firms only; therefore, we cannot include non-manufacturing firms backed by Innofund, thus reducing the number of Innofund-backed firms in the sample. Non-state-owned firms with sales of less than RMB 5 million are also not included in the ASIFP. Hence, we may have missed several micro-sized firms backed by Innofund. One of the aims of the study is to estimate the ex-post effects of Innofund. An Innofund-backed firm that lacks information on the year when it received funding is also excluded. Theoretically, we included all state-owned manufacturing firms supported by Innofund and non-state-owned manufacturing firms with more than 5 million RMB in sales (in the year of application) backed by Innofund for the estimations.

administrative region. Moreover, a company has an exclusive right to its name on a regional basis. Thus, if the Chinese name, location, and industry of a company are shown exactly the same in both databases in the same year, then it must be identified as the same company. Year is an important factor to secure the accuracy of the matching. Firms are considered identical only when the firm names can be matched in the same year shown in both databases. Moreover, to prevent type II errors in matching, we apply computerized matching by replacing the "standard names" with "stem names" and manual matching. Such procedures prevent the matching quality from being affected by the variations in firm names shown in the two databases.

Finally, our matching quality would also be unaffected by the variations or changes of firm names over time. First, the final panel database for Innofund-backed firms is not built up by firm names. Rather, we establish the panel by legal person codes of firms based on the cross-sectional data matched by firm names and other information by year. According to the China's Company Registration Rules, the legal person code of a company is unique nationwide and will not change after the registration of a legal entity even if its name or business nature is changed. By using the legal person codes, we identified firms by year to match and build up the panel database. Thus, the changes of firm name over time cannot affect the matching quality.

Table 1 presents the distribution of the sampled Innofund-backed firms. Panel A shows the industry distribution of Innofund-backed firms. Innofund support is concentrated mainly on eight industries that belong to high-tech industries as defined by the National Bureau of Statistics. A total of 81% of the sampled Innofund-backed firms belong to high-tech industries. The allocation of Innofund is consistent with the goal of government R&D programs to support corporate R&D activities. Panel B

presents the year distribution of Innofund-backed firms on the basis of the time they received their first round of Innofund grant. We show the distribution of awarding year for the sampled Innofund-backed firms in this study and the full sample of Innofund-backed projects. Results show that from 1999 to 2007, the sampled Innofund-backed firms have similar year distributions -like those in the full sample, thereby suggesting the representativeness of our sample in this aspect.

This study also needs to match the firms in the ASIFP database with those in the SIPO patent database to identify patent information for all firms in the estimations. In general, three types of patents exist in China, namely, invention, utility, and design patents. Invention patents are subject to examinations similar to those conducted in other major patent offices in the world. This type of patent is given 20 years of protection and may be granted to the methods and products. Both utility and design patents are given 10 years of protection. Utility patents are generally granted to technical solutions related to shapes or structures, whereas design patents are normally granted to shapes and patterns with patentable aesthetic appeal. Firms have to exert considerable effort to generate patentable materials, although invention patents are the most technologically innovative and thus require more R&D efforts than the two other types. In this study, we measure patent outputs using two values: the number of invention patents and the number of patents of all types granted to a firm in a given year. Given that creating patentable works and applying for a patent take time, we use filing time of newly granted patents as a basis in panel estimations. We also use the one-year lag of filing time for all estimations to check the robustness of the results.

The matching strategy we apply to match ASIFP and SIPO is significantly similar to that which is used to match the name lists of Innofund-backed firms and the ASIFP. However, the major difference is that SIPO does not provide information for the industry of a firm that we do not control in the matching. However, this issue will not affect the quality of our matching. As we discussed earlier, firm names, location and year are the details that are needed to secure the accuracy of the matching.

A potential concern with patent matching is the potential miscount of patents for the subsidiaries of firms. According to the Patent Law of China, organizational patent applicants must provide the registration license while applying to file a patent, thereby suggesting that a firm that applies for patents must be an independent legal entity. Patents applied by subsidiaries that are not registered as independent legal entities will be filed to the parent firm. Similarly, only an independent legal entity will be recognized as an individual firm. Therefore, our matching approach, which is based on both the names and locations of firm (for cross-sectional data matching by year) and legal person codes (for panel construction), should not be affected negatively by miscounts for firm subsidiaries.

3.2 Sampling: PSM

We estimate the effects of Innofund on firm innovation outputs by constructing a control group of non-Innofund-backed firms. We build the control group with several steps to ensure that our results are not driven by a specific matching method and control for selection biases. We first identify firms that are eligible to apply for Innofund but did not apply or did not win the grant from the ASIFP Database. The Innofund selection criteria are officially announced each year.

A firm is eligible for Innofund application if its SIC [7] is similar to the SICs of the awarded group, has fewer than 500 employees, and has a leverage ratio lower than 70%. The Innofund program also requires that R&D investments of a firm should be more than 3% of the total sales, and the number of R&D employees should be more than 10% of the total number of employees.[8]

After identifying all eligible firms, we utilize a PSM algorithm proposed by Rosenbaum and Rubin (1985) to construct the control group on the basis of the identified pool of eligible firms. In the context of our study, the propensity score refers to the predicted probability of a firm to receive Innofund support. According to the screening criteria of Innofund program introduced in Section 2, firms with potential to generate high economic and social benefits, firms with leading products in the market, firms with projects that utilize new and advanced technologies or with independent intellectual property rights and high value added, and projects that utilize new and advanced technologies will be prioritized. That is, innovation potentials are the major consideration when Innofund selects projects to support. Therefore, innovation performance is our major focus in designing the PSM algorithm. When non-Innofund-backed firms are constructed on this propensity score, we ensure that the matched non-Innofund-backed firms are selected based on their two-digit SIC industry code, location, size, leverage ratio, sales from new products, exports, and stock of patents. Following the suggestion of Démurger et al. (2002), we control the location to capture disparities in regional growth rates and levels of development, which may affect the results. We also match the size and leverage ratio of Innofund-

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[7] The National Bureau of Statistics in China updated the SIC system in 2003. Thus, we amend the two-digit SIC before 2003 to maintain consistency with the latest code system.

[8] ASIFP does not provide information on human capital and presents only data on R&D investment from 2005 to 2007. Thus, we cannot utilize the R&D investment and human capital information as criteria for the control group sample construction.

backed firms and their counterparts. These criteria ensure that Innofund-backed and non-Innofund-backed firms are similar in many aspects, which may affect the probability of being supported by Innofund and their innovation outputs in the future. Specifically, we use one-to-five nearest-neighbor PSM to identify non-Innofund-backed firms. We also impose common support restrictions during matching. [9] Moreover, to assess matching quality, we check whether significant differences in relevant variables between Innofund-backed and matched non-Innofund-backed firms can be found by following Rosenbaum and Rubin (1985). Table 2 presents the results of the balance tests of both the randomly drawn sample[10] and the PSM matched sample on major innovation measurements. T-statistics indicated that the relevant variables are balanced between the Innofund-backed firms and the PSM matched sample. [11]

The major shortcoming of the ASIFP database that affects our PSM is that ASIFP provides data on R&D expenditure only from 2005 to 2007 and does not provide detailed information on human capital. Thus, we cannot utilize R&D investment and information on human capital as criteria to construct the control group sample. However, given that R&D expenditure is one of the most important factors that may affect innovation outputs, we utilize R&D investment information as criteria to match a subsample of Innofund firms that obtained funding in 2005 and 2007 to check the robustness of the results (see Section 4 for details).

Table 3 shows the summary statistics of Innofund-backed and non-Innofund-backed firms in the PSM control group, including the number of observations, mean,

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[9] Our results are robust after we remove the common support restrictions.
[10] We construct a randomly draw sample of the control group and present the difference between the sample matched by PSM approach and the randomly draw sample to further justify why we have to employ the PSM sample in order to reduce the selection biases.
[11] The balance tests for other variables are available upon request.

maximum, and standard deviations across the entire examination period. On average, Innofund-backed firms have higher innovation outputs in terms of the number of newly granted patents and sales from new products. Similarly, these firms are younger and larger in size as measured by total sales and total assets. These firms also have lower liability compared with non-Innofund-backed firms. No considerable difference was observed in exports between the two groups.

4. Does Innofund Affect Innovation Outputs?

In our subsequent analysis, we examine whether the Innofund Program stimulates innovation outputs. First, we compare the innovation outputs of Innofund-backed firms with those of non-Innofund-backed firms. Second, we examine whether the amount of Innofund grant is associated with innovation outputs. Finally, we address the identification issues using two-stage regression models.

4.1 Innovation Outputs of Innofund-backed and Non-Innofund-backed Firms

We test whether the Innofund Program helps firms generate more innovation outputs by implementing fixed effect panel data regression through the following basic regression models:

$$y_{it} = \alpha_0 + \beta x_{it} + \delta InnoAft_{it} + e_i + e_t + e_{it} \qquad (1.1)$$

$$E(y_{it}|x_{it}, e_i, e_t) = \alpha_0 + \beta x_{it} + \delta InnoAft_{it} + e_i + e_t + e_{it} \qquad (1.2)$$

where i indices a firm, t indices time, and y_{it} are dependent variables used to measure the innovation output of firm i at time t. The innovation outputs include sales from new products, exports, and newly granted patents. *InnoAft_{it}* is a dummy variable equal to 1 if the firm gained Innofund support at time t and equals zero if otherwise. A

vector of control variables is indicated by x_{it}. e_i controls time-invariant firm-specific unobserved variables, and e_t controls yearly fixed effects. The effect of Innofund on innovation outputs is represented by δ. We use a fixed effect panel data model to estimate (1.1) when the dependent variables are exports, sales from new products, and patent counts in log-link formulation. We utilize a logit model for panel data to estimate (1.2) when the dependent variables are dummy variables of sales from new products and exports. The standard errors for correlation are adjusted within the cluster in all models (Petersen, 2009).

Table 4 presents the results on the effects of Innofund on innovation outputs of firms. Models (1) to (4) show that $InnoAft_{it}$ is significantly and positively associated with sales from new products and exports of firms, whether these values are measured by absolute figures or dummy variables. These findings suggest that Innofund-backed firms generate significantly higher sales from new products and exports after gaining government support compared with non-Innofund-backed firms and the same firms before funds were infused. Meanwhile, the probability that Innofund-backed firms generate sales from new products and exports is significantly higher than that of non-Innofund-backed firms and the same firms before the funds were infused. For example, Model (2) shows that, given the other things being equal, the probability that a firm generates sales from new products will increase by 7.88% after the firm wins Innofund support. Similarly, Model (4) shows that winning Innofund support can help to increase the probability that a firm generates export by 2.41%.

Models (5) and (6) present the estimations of how Innofund affects newly granted patents and show that Innofund significantly and positively motivates firms to

generate more patents. We examine both the number of patents of all types and the number of invention patents in logarithm format. The coefficients of $InnoAft_{it}$ in Models (5) and (6) are significantly positive, thereby indicating that Innofund-backed firms generate more new patents of all types and more invention patents after winning Innofund support compared with non-Innofund-backed firms and the same firms before the grant. For instance, Model (5) shows that the growth rate of newly granted patents of all types for Innofund-backed firms after the grant is 13.2% higher than that of non-Innofund-backed firms and the same firms before winning the grant. Model (6) shows that the growth rate of newly granted invention patents for Innofund-backed firms after the grant of funds is 8.6% higher than that of non-Innofund-backed firms and the same firms before the grant. In summary, Table 4 shows that Innofund effectively influences the innovation outputs of awarded firms. Our results remain the same when we use the one-year lag for patent filing time.

The monetary effect of the funding is also examined. The estimation focuses on the total amount of Innofund support given to firms. Thus, we may obtain more insightful ideas on the extent to which government R&D funding addresses the financial constraints of firms in China where resource allocation is biased. The amount of funding (***InnoAmt$_{it}$***) is used to replace $InnoAft_{it}$ in Equations 1.1 and 1.2. The results are presented in Table 5. Models (1) to (4) show that ***InnoAmt$_{it}$*** is significantly and positively correlated with the sales from new products and exports of firms. These findings imply that firms that win a larger Innofund grant may generate significantly higher sales from new products and exports. Meanwhile, the probability of generating sales from new products and exports increases as the size of Innofund support increases. For example, Model (2) shows that if a firm wins a funding of

1 million RMB, then the probability that the firm generates sales from new products increases by 11.73%. Similarly, Model (4) shows that if a firm wins a funding of 1 million RMB, the probability that the firm generates export increases by 2.63%.

Model (5) shows that after winning a funding of 1 million RMB, the growth of newly granted patents of all types generated by Innofund-backed firms is 20% higher than that of non-Innofund-backed firms and the same firms before the grant. Model (6) shows that a funding of 1 million RMB results in the 10% higher growth of newly granted invention patents generated by Innofund-backed firms compared with non-Innofund-backed firms and the same firms before the grant. The results shown in Table 5 imply that the amount of Innofund support affects the innovation outputs of firms significantly.

We further examine the effects of the relative weights of the funds. The ratio of Innofund support over total free cash of the firm is used to replace *InnoAmt$_{it}$*, and the regressions conducted in Table 5 are repeated. However, the results show that the abovementioned relative measure does not affect the innovation outputs of firms significantly (results are provided upon request).

R&D input is an important factor that may affect the grant of funds. However, the ASIFP database does not provide complete information on the R&D expenses of firms and only contains information for 2005, 2006, and 2007. Hence, a subsample analysis is conducted to test whether our results are biased because of the missing information. We focus on firms that obtained their first round of Innofund funding in 2006 and 2007. Innofund-backed firms are matched with non-Innofund-backed firms in the year prior to the awarding of the Innofund grant on the basis of the two-digit SIC industry code, location, total sales, exports, sales from new products, number of

patents, and R&D expense. Estimations in Table 4 are duplicated based on the newly matched subsample. The results are presented in Table A-2, which shows that our main conclusion remains the same after we control R&D input in the PSM process.

4.2 Identification

We have shown that Innofund-backed firms outperform non-Innofund-backed firms in terms of sales from new products, exports, and newly awarded patents after potential ex-ante selection effects are controlled using the PSM approach. One significant limitation of the PSM methodology is its inability to determine the effects of unobservable variables. Missing variables instead of Innofund may contribute to improved innovation outputs. For instance, we could not measure the R&D ability of firms or observe the management capability of executives on the basis of existing data. However, both factors may contribute to the innovation outputs of the firms.

We use two-stage estimations to address the abovementioned identification concerns. A proper IV must be correlated to the endogenous variable but unrelated with unobserved variables that may affect dependent variables. The first IV used is the total number of firms in high-tech zones of the city where the firm is located in each given year (*Frm_HTZ*). High-tech zone is a distinctive type of special economic zone (SEZ) in China where central and local governments seek to attract foreign direct investment and consequently stimulate the development of the local economy. Information on the number of firms in high-tech zones at city level is obtained from the China Statistical Yearbook on Science and Technology (1999–2007). The second IV is the ratio of total investment in fixed assets made by local governments over the total GDP at the county level each year (*Fxd_Asst*). Information on local government

investment across 1998 to 2007 is obtained from city yearbooks. Both IVs reflect the effort level of the local governments in the developing local economy. We suggest that these two IVs can help to identify the probability of a firm winning an Innofund grant. However, the IVs should not be directly correlated with the error terms that affect the innovation outputs of individual firms.

The choice of the two IVs is mainly based on the understanding in institutions in China. Under the regionally decentralized authoritarian regime in China, the central government governs the state through personnel control, whereas local governments manage economic activities and allocate resources (Xu, 2011). During the economic reform era, local governors compete with each other in terms of economic growth, the search for resources, and support from the central government to obtain promotion opportunities. The success rate of local Innofund applications is one of the performance assessment criteria of local governments. Thus, more ambitious local governments are more likely to support local firms in competing for the Innofund program and to exert more effort in lobbying the upper-level governments for local firms to win Innofund grants. The level of effort of local governments in attracting foreign investment and investing in fixed assets is a good indicator to measure how ambitious the local governments are. We consequently expect the two IVs to be positively correlated to the probability a local firm winning Innofund.

However, the two IVs should not be directly correlated with the error terms of estimations on innovation outputs of individual firms. The two IVs used are measured either at the city level or county level, whereas innovation outputs are measured at the firm level. That is, we should not expect a direct relationship between the measurements of different levels unless externalities from high-tech zone

development at city level or investment in fixed assets at county level exist. In particular, a potential argument is that innovative firms may tend to cluster geographically and consequently generate externalities to each other. However, empirical analysis on the spillover effects of high-tech zones or SEZs in China is limited, and results are mixed. Several studies find that the establishment and development of SEZs significantly and positively affects foreign direct investment, physical capital, exports, or outputs of foreign firms at the city or province level (Cheng and Kwan, 2000; Wang, 2013; Alder et al., 2013). However, Hu (2007) did not obtain evidence of the geographical externalities of high-tech parks. Meanwhile, on the basis of firm-level data, Schminke and Van Biesebroeck (2013) reveal that firms within SEZs do not generate higher total factor productivity. The existing literature suggests that the relationship between the IVs we use and the innovation outputs of individual firms may be unclear. Thus, we statistically test the exogeneity of the IVs by conducting overidentification estimations (Sargan, 1958).

Results of the two-stage estimations are reported in Table 6. Panel A of Table 6 presents the results from the first stage of estimation. The results demonstrate that the number of firms in local high-tech zones and the investment in fixed assets made by local governments are significantly and positively correlated to whether a firm wins Innofund backing at a given year. These results suggest that a firm has a greater probability of receiving Innofund support when it is located in a city or county where local governments are more ambitious and provide more support to local firms. The first stage of estimations confirms the relevance of the instrumental variables.

The results of the second stage of estimation are presented in Panel B of Table 6. Sargan tests are performed to test the exogeneity of the two IVs. The results of the

Sargan tests indicate that the null hypothesis, which states that the two instrumental variables are uncorrelated to the residuals, cannot be rejected for all estimations. Thus, the results statistically prove that both the IVs satisfy the conditions of qualifications as IVs. Models (1) to (2) indicate that firms generate more sales from new products after they obtain Innofund grants compared with non-Innofund firms and the same firms before receiving Innofund support. Similar results are observed in the number of newly granted patents of all types and the number of newly granted invention patents. The outcomes of two-stage estimations are consistent with the regression results in Tables 4 and 5. These outcomes empirically confirm that winning Innofund support positively affects innovation outputs, even after considering the endogenous nature of Innofund.

5. Innofund Governance and Innofund Effects

The governance of the Innofund Program experienced a significant change in 2005 because of policy shock (Section 2). The major feature of this change is that the central government substantially delegated the decision making power in project screening to local Innofund offices. R&D projects are associated with a high level of uncertainty. Thus, any investment in such projects, including government R&D funding, depends significantly on screening mechanisms. Hence, we investigate whether the change in ex-ante screening systems may influence the effects of Innofund on the innovation outputs of the firms.

Discussions on the relationship between the quality of project selection and the organizational structure are abundant. The rationality of human beings is limited. Moreover, information gathering, transmission, and processing are costly. Sah and Stiglitz (1991) argue that centralized organizations may delay decision making and

reduce the total number of projects because of cost constraints and the lack of local information unlike decentralized screening systems. Following the information approach, Aghion and Tirole (1997) and Hart and Moore (2005) further emphasize that a decentralized decision making system may strengthen the incentives of local agents in acquiring information and may reduce the overload problem experienced by the principal. Stein (2002) predicts that decentralized organizations are more attractive when the needed information is "softer" (i.e., the information is difficult for outsiders to verify), whereas centralized organizations are more favorable when the needed information can be "hardened" (i.e., the information is easier to verify) without cost.

Another strand of research on the organization of decision making is mainly derived from soft budget constraints theory. Dewatripont and Maskin (1995) suggest that a centralized credit market may affect efficiency because of adverse selection and the lack of a termination mechanism. Qian and Xu (1998) further posit that bureaucracy often results in more mistakes through the rejection of promising projects, thus delaying innovation. Decentralized decision making may not only reduce ex-ante screening costs but may also terminate bad projects ex-post that both types of errors may reduce. Thus, decentralized organizations may increase the number of selected projects and reduce errors in accepting or continuing when investing in innovation to refinance bad projects. This effect should be more obvious in investment when the uncertainty is higher, and the quality of the projects is more difficult to predict ex-ante.

Empirically, firm-level estimations demonstrate a strong and positive relationship between R&D investment decisions and the decentralization of the organizational structure. Rajan and Wulf (2006) show a strong movement towards flatter corporations in the U.S. Caroli and Van Reenen (2001) report a positive

association between decentralization and the development of IT adoption. Acemoglu et al. (2007) find that, apart from younger firms, more technology-oriented firms are more likely to choose decentralization. The aforementioned studies focus on the efficiency of the decision making processes and the organizational forms of for-profit organizations. However, none of them investigates the relationship between decentralization or organizational change and investment decision making for public subsidy programs.

The existing literature suggests the potential consequences of the change of Innofund governance in 2005. These projects are expected to be associated with a high level of uncertainty and severe information-related issues because the Innofund program targets young firms with potential advanced technology in some frontier industries. Thus, the efficiency of the information passage and incentives of local knowledge holders (i.e., local Innofund offices in our context) are important for project selection. The major policy change in 2005 was to delegate more decision making power to local Innofund offices. Local Innofund offices had no input in the final decision of the awardees before 2005. After 2005, their views have 30% weight in the final decision of the awardees. Moreover, the ex-ante funding commitment after 2005 further enhanced the alignment of interests between the local and central Innofund offices. Therefore, this policy change may significantly affect the incentives of local Innofund offices and the effects of Innofund. Indeed, as introduced in Section 2, local Innofund offices took more initiative to experiment with new approaches in project selection after 2005. On the basis of existing literature (Dewatripont and Maskin 1995; Qian and Xu, 1998; Ahgion and Tirole, 1997; Hart and Moore, 2005), the decentralized screening system after 2005 is expected to help in selecting better-quality projects and consequently have stronger positive effects on firm innovation

outputs compared with the centralized screening process before 2005. Moreover, the magnified effects of Innofund after 2005 are expected to be stronger on the technological innovations of firms.

To test whether the Innofund effects on innovation changed significantly after the change of Innofund governance, a series of regressions for innovation outputs is conducted by distinguishing firms backed by Innofund before and after 2005, along with their non-Innofund-backed counterparts. The regression equations are listed below.

$$y_{it} = \alpha_0 + \beta x_{it} + \delta_1 Inno\_2005Bef_{it} + \delta_2 Inno\_2005Aft_{it} + e_i + e_t + e_{it} \quad (2.1)$$

$$\begin{aligned} E(y_{it}|x_{it}, e_i, e_t) \\ = \alpha_0 + \beta x_{it} + \delta_1 Inno\_2005Bef_{it} + \delta_2 Inno\_2005Aft_{it} + e_i + e_t \\ + e_{it} \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad (2.2) \end{aligned}$$

where all the variables remain the same as those in Equations (1.1) and (1.2), and the Innofund dummy variable is replaced with two dummy variables to specify the Innofund-backed firms before and after 2005. *Inno_2005Bef$_{it}$* is a dummy variable that is equal to 1 if the firm has gained Innofund support at time t, and the support was granted before 2005; otherwise, the dummy variable is equal to 0. *Inno_2005Aft$_{it}$* is a dummy variable that is equal to 1 if the firm has gained Innofund support at time t, and the first Innofund has been granted after 2005; otherwise, the dummy variable is equal to 0.

Table 7 reports the regression results for the effects of the change in the screening system. Models (1) to (2) show that *Inno_2005Bef$_{it}$* and *Inno_2005Aft$_{it}$* are significantly and positively correlated with the sales from new products measured by

log-link formulation of absolute number and dummy variable. The results are consistent with the findings shown in Table 4. To test the significance of the policy change effects, we conduct Lincom tests and statistically examine the difference of the coefficients of $Inno\_2005Bef_{it}$ and $Inno\_2005Aft_{it}$. However, the Lincom tests suggest that the difference between the two coefficients is statistically insignificant although the coefficients of $Inno\_2005Aft_{it}$ are larger than those of $Inno\_2005Bef_{it}$ in Models (1) and (2). Models (3) to (4) present the estimations for exports. The results are similar to those that we observed with the sales from new products. Models (1) to (4) indicate that the effects of Innofund on commercialized innovation outputs do not seem to significantly change after 2005 when the governance of the government R&D program was changed.

The findings shown in Models (5) and (6) are different. The models show that $Inno\_2005Bef_{it}$ and $Inno\_2005Aft_{it}$ are significantly and positively associated with newly granted patents of all types and invention patents. Moreover, the coefficients of $Inno\_2005Aft_{it}$ are consistently and significantly larger than those of $Inno\_2005Bef_{it}$ in both regression models. Model (5) indicates that after gaining Innofund support, the growth of newly granted patents of all types generated by Innofund-backed firms selected before 2005 is 11.4% higher than that of non-Innofund-backed firms and the same firms before winning the grant. The growth of newly granted patents of all types by Innofund-backed firms selected after 2005 is 16.2% higher than that of non-Innofund-backed firms and the same firms before winning the grant. Model (6) demonstrates that after winning the Innofund grant, the growth of newly granted invention patents generated by Innofund-backed firms selected before 2005 is 7.6% higher than that of non-Innofund-backed firms and the same firms before winning the

grant. After the firms win Innofund support, the growth of newly granted invention patents by Innofund-backed firms selected after 2005 is 10.1% higher than that of non-Innofund-backed firms and the same firms before winning the grant. Moreover, the Lincom tests statistically confirm that the growth of both newly granted patents of all types and invention patents is significantly higher for firms that win the Innofund grant after 2005.

These findings suggest that the significant improvement of Innofund effects on technological innovation outputs after the governance of Innofund was systematically changed in 2005. However, the policy change in 2005 does not seem to affect the commercialized innovation outputs of the firms.

A few alternative mechanisms may exist for the results of the 2005 effects. For instance, the property rights protection was improved since 2004, which may be one of the alternative mechanisms that helped enhance the effects of Innofund.[12] With better protection of private property rights, firms may have stronger incentives to invest in R&D activities after 2004 than before in general. Second, the improved protection for intellectual property rights since 2003 may also contribute to the enhanced Innofund effects after 2005.[13] Given that IPR is an important system that protects and promotes R&D investment, the improved IPR protection in China since 2003 may stimulate investment in corporate R&D activities.

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[12] Specifically, in 2004, the state constitution of China was amended, and the protection of private property rights was constitutionalized for the first time. Although the private sector was legally recognized in the mid-1990s, the protection of private rights was not recognized by the constitution until 2004.

[13] Starting from 2003, China and the United States have held a round-table conference on IPR every year, and they have reached agreements on many IPR-related issues at two round-table conferences. In 2004, China and Europe held their first round of talks on IPR in Beijing, and an initial agreement was reached between the two sides on matters of cooperation related to IPR. With more interactions and cooperation with US and Europe, the enforcement of IPR protection was significantly improved in China. Statistics have shown a sharp increase in patent application. Patent applications in China had exceeded two million by March 17, 2004. It took China 15 years for patent applications to reach one million. However it took only four years for the number to double from 2000 to 2004.

The abovementioned two institutional changes may be relevant to the enhanced Innofund effects observed after 2005. However, these institutional elements should have effects on Innofund-backed and non-Innofund-backed firms at the same time, although the marginal effects may be different for the two types of firms. Nevertheless, in our panel estimations, we observe the before-and-after changes and the differences between Innofund-backed firms and non-Innofund-backed firms in terms of innovation outputs while using 2005 as a cut-off. Moreover, as shown in the data, the rejection rate of Innofund application significantly decreased after 2005, thus suggesting that the local IAC becomes more careful in project selection when it has more decision-making power in project screening and needs to commit the matching funds upfront. Therefore, we suggest that the change of governance of Innofund is a more direct factor contributing to the enhanced Innofund effects after 2005. The results are consistent with the arguments of Dewatripont and Maskin (1995), Ahgion and Tirole (1997), and Qian and Xu (1998). These researchers propose a more decentralized screening system for investing in R&D-oriented projects when the degree of uncertainty is higher and the information issues are more severe.

6. Conclusion

This paper estimates the effects of Innofund on the innovation outputs of firms. Innofund is one of the largest Chinese government programs that target corporate R&D activities of SMEs in China. We examine how the governance of such a program influences the effects of Innofund aside from its general effects on the innovation outputs of firms.

Innofund-backed firms generate significantly more innovation outputs compared with non-Innofund-backed firms and the same firms before Innofund funding was infused. We use PSM methodology to control the selection issues. The results remain robust after using two-stage Heckman estimations to further address the identification problems. These findings are consistent with several existing studies, which argue that government funding stimulates corporate R&D activities (Irwin and Klenow 1996; Griliches and Regev, 1998; Audretsch et al., 2002; Lach, 2002; Görg and Strobl, 2007). Furthermore, Innofund effects differ before and after 2005 when governance of Innofund was shifted. The effect of Innofund support on the technological innovation outputs of firms further improved after 2005 when project screening became more decentralized. These results are consistent with the findings reported by Dewatripont and Maskin (1995), Ahgion and Tirole (1997), and Qian and Xu (1998).

This study provides a new perspective for evaluating government R&D policy. We extend the existing studies on government R&D programs by looking further at the governance of the government R&D programs and their influence on the effects of such programs that have been largely neglected by extant literature. Meanwhile, as a first systematic examination of government-supported corporate R&D programs in China, this study extends the extant literature by exploring how the market failures and the government engagements interact under weak institutions in China. Finally, this study is also related to the literature on general R&D financing mechanisms by exploring the governance of the financial institutions and the effects of the investment.

This study has important policy implications. The findings of this study suggest that decentralized governance may ease the information issues and motivate

local governments to exert more effort in project selection and ex-post monitoring activities, thus improving the effects of government R&D programs. Moreover, the Chinese government has continually emphasized the role of innovation in fostering a sustainable economy and allocated public funds at an accelerating rate to support R&D activities. Driven by government policy, China's R&D expenditure has grown into the second largest worldwide since 2010 (WSJ, 2010) and is expected to become the largest worldwide by 2022 (KPMG, 2013). China's current R&D expenditure over GDP ratio is higher than that of the European Union (Noorden, 2014), and its total number of patent applications has surpassed that of the U.S. since 2011 (KPMG, 2013). [14] Public support for industrial innovation in China is a major topic in international political economy because it determines the sustainability of China's growth and affects the competitive landscape of the global economy. However, solid empirical analysis on the consequences of public support has yet to be conducted. This assessment of Innofund program and its governance should have some important policy implication on how we view the innovation capacity in China.

This study also raises several questions for further research. First, if government R&D programs indeed contribute to the innovation outputs of the firms, are innovation outputs simultaneously transferred to improvements in the productivity or profitability of the firms? Second, can other mechanisms (e.g., property right institutions, IPR protection, financial budget constraints [Qian and Xu, 1998; Huang and Xu, 1999], product competition, and input markets or trust and relationships

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[14] Noorden, Richard Van, 2014, "China tops Europe in R&D Intensity," Nature, 08 Jan. 2014, (http://www.nature.com/news/china-tops-europe-in-rd-intensity-1.14476); WSJ,2010,"China Surpasses Japan in R&D as Powers Shift," Wall Street Journal, 13/12/2010; KPMG, 2013, "Innovated in China: New Frontier for Global R&D,"
(http://www.kpmg.com/CN/en/IssuesAndInsights/ArticlesPublications/Newsletters/China-360/Documents/China-360-Issue11-201308-new-frontier-for-global-R-and-D.pdf)

[Allen, et al., 2012]) influence the effect of government R&D funding? If so, how do different mechanisms work together or interact with one another? Third, do the effects of different forms of government R&D programs vary? If so, what are the explanations or mechanisms for the observed differences? Finally, do government R&D programs have spillover effects?

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