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What Types of Science and Technology Policies Stimulate Innovation? Evidence from Chinese firm-level data*

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Abstract

Since the Chinese government's rapid increase in expenditure on science and technology (S&T) during the 2000s, numerous related policies have been implemented by national-, provincial-, city-, and prefecture-level governments in China. Each level of government aims to promote innovation activities; however, few empirical evaluations have been conducted on each policy level and category. This paper estimates the treatment effects of innovation policies at each government level and category by using firm-level survey data from the inland city of Chengdu. Results suggest that S&T policies stimulate effective firm-level innovation activities; in particular, city-level policies and various government services. On the other hand, some policy categories, including tax incentives, seem to be inefficient. Restructuring the current policy menu and establishing further feedback mechanisms for S&T policy will improve the efficacy of such spending.

*Keywords***:** Chinese innovation system, Innovation policy, Policy evaluation
JEL classification: O31, O32, O38, O53

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1. Introduction

Due to the critical role of innovation activities for economic growth (Grossman and Helpman, 1991) and the existence of market failures in private research and development (R&D) activities (Arrow, 1962), many national governments have implemented various technology and innovation policies (OECD, 2010). Since the 2000s, many emerging economies have also established ambitious goals and related policies. China is a typical emerging giant in the field of science and technology (S&T). The Chinese government rapidly accelerated its S&T expenditures; the annual growth rate of R&D was nearly 19% between 1995 and 2005, a rate that was considered "exceptional" (OECD, 2009). OECD (2009) provides a comprehensive picture of the Chinese innovation system, including its institutional framework, major indicators, and historical background. Several other studies have also been conducted to understand Chinese innovation activities and policies. Breznitz and Murphree (2011), for example, examined the Chinese innovation system with particular attention to the regional viewpoint; namely, focusing on the role of local government, universities, institutions, and private firms.

Although this research provides a detailed and comprehensive picture of the Chinese innovation system, the research should also include an empirical evaluation of policy programs. Almus and Czarnitzki (2003), for instance, used survey data and the propensity score matching method to evaluate the treatment effect of R&D subsidies in eastern Germany. They found an approximately 4% increase in R&D intensity due to the policy treatment. González and Pazó (2008) estimated a similar policy effect on R&D expenditure in the case of Spanish manufacturing and Clausen (2009) investigated a similar case in Norway, using a two-stage regression model.[1] In the case of China, Wang et al. (2014) estimated the treatment effect of R&D subsidies on R&D expenditure using a firm-level dataset for Shanghai, and found a positive stimulation effect of government subsidies. They also reviewed empirical papers written in Chinese and reported positive stimulation effects in 8 of 11 studies. Although there is a consensus that Chinese innovation policy has a positive stimulation effect, an important question remains open for discussion; namely, what type of S&T policies works better? Since the Chinese innovation policy system has "multi-level and multi-route" features, as we discuss later, it is important to examine the treatment effect by policy level and category. To answer this research question, we empirically evaluate various policy effects using detailed firm-level policy data collected by a city-level government in China in 2012.

The *Oslo Manual*, an international guideline for innovation surveys, defines innovation as "the implementation of a new or significantly improved product (good or service) or process, a new

1 See a review of the R&D subsidies effect by David, Hall, and Toole (2000) for studies conducted by the 1990s. Many of these papers focus on the crowding-out effect of public subsidies; however, we focus on the treatment effects by policy level and category because our dataset does not allow us to evaluate R&D expenses.

marketing method, or a new organizational method in business practice, workplace organization, or external relations" (OECD, 2010, p. 11) that mainly focuses on relatively discontinuous innovations. As China is a middle-income economy, this paper focuses on incremental innovation activities.

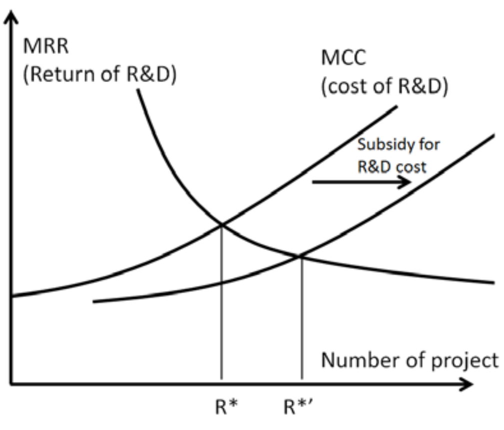
The remainder of the paper is organized as follows. Section 2 provides an overview of the Chinese innovation policy and its national innovation system, with particular attention to city-level activities. Section 3 presents the methodology used to estimate the policy effects and our firm-level dataset. Section 4 reports our estimation results and Section 5 concludes the paper.

2. Theory on R&D and policymakers in China

2.1 R&D decisions at the firm-level and their policy effects

Before focusing on the Chinese innovation systems and policies, it is valuable to understand the basic mechanism of innovation policy. David et al. (2000) present a simple model of R&D decisions in Figure 1. The horizontal axis represents the number of R&D projects a firm conducts in a given period. The vertical axis represents the cost and return of the R&D projects. The downward-sloping curve indicates the marginal return of the R&D projects (MRR) and the upward-sloping curve indicates the marginal cost of R&D capital (MCC). Under the assumption of firm rationality in terms of the costs and benefits of R&D, a firm conducts R&D projects at the level R*. Here, direct R&D subsidies or cost-sharing programs by the government reduce the R&D costs and shift the MCC schedule to the right. Public demand subsidies, including government procurement or consumer price reductions, also shift the MRR schedule to the right increasing the R&D project returns. In both cases, firms are able to conduct additional projects at the level R*'.

Figure 1. Firm-level decisions of R&D projects



Source: David et al (2000).

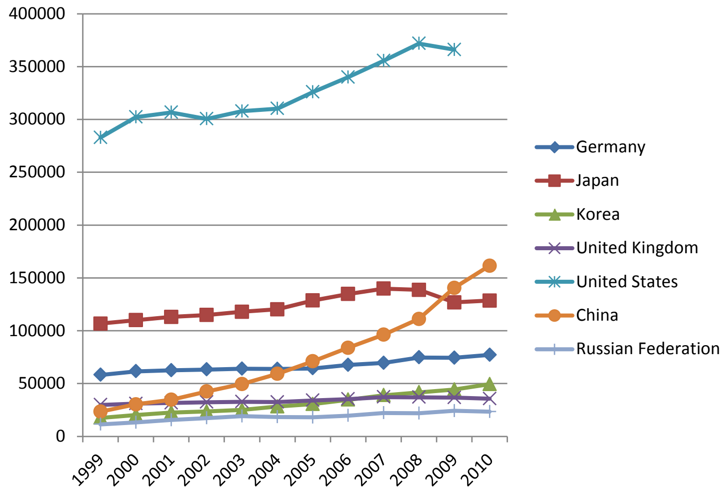
Regarding the types of innovation policies, according to Steinmueller (2010), technology and innovation policies can be divided into four categories—supply-side policies, demand-side policies, policies for complementary factors, and institutional policies. According to certain criteria, supply-side policies are one of the most direct approaches to subsidizing or funding firms; meanwhile, such subsidy attempts shift the MCC schedule to the right. In addition, some particular industries or regions are often chosen. In contrast, demand-side policies attempt to raise the return of new technology and products by reducing the price of innovative goods. For example, subsidies for alternative energy technologies, such as electric vehicles, shift the MRR schedule to the right. The complementary policies comprise attempts to increase the skilled workforce and improve technology information, reducing the cost of firm-level R&D. The institutional policies try to stimulate innovative activities by coordinating the institutions and agencies. As Liu et al. (2011) examined, the Chinese government implemented 79 policies during the 2006–2008 period and a large portion of these policies were direct, supply-side support policies through various channels, including subsidies for firm R&D activities and patents, as we discuss later.

2.2 Policy initiatives and actors in China

The Chinese national government has aggressive plans to promote S&T activities and innovations by various channels. The "National Guidelines for the Medium- and Long-term Plan for Science and Technology Development (2006–2020)" (MLPST) is the most comprehensive policy document, emphasizing "indigenous innovation" (自主创新, *Zizhu Chuangxin*) and targets the achievement of an R&D/GDP ratio exceeding 2.5% by 2020. As shown in Figure 2, Chinese R&D expenditure increased rapidly and continuously during the 2000s, and surpassed that of Japan in 2009. China's R&D ratio to GDP was 1.32% in 2005 and it rose to 1.77% in 2010.[2] On the basis of China's national plan, its R&D expenses may exceed those of the United States during the 2020s or even earlier. During the 2000s, the Chinese government (both national and local governments, including the provincial-, city-, and lower-levels) substantially accelerated S&T–related expenditure from 57.5 billion renminbi (RMB) in 2000 to 411.4 billion RMB in 2010, where it doubled from 2006 to 2010 after the introduction of the MLPST policy document.[3] In 2011, the national government spent 246.9 billion RMB, whereas local governments spent 243.3 billion RMB, which is almost equivalent to the national budget.

[2] Data from *China Statistical Yearbook on Science and Technology,* 2012, p. 246.
[3] Data from *China Statistical Yearbook on Science and Technology,* 2012, p. 15.

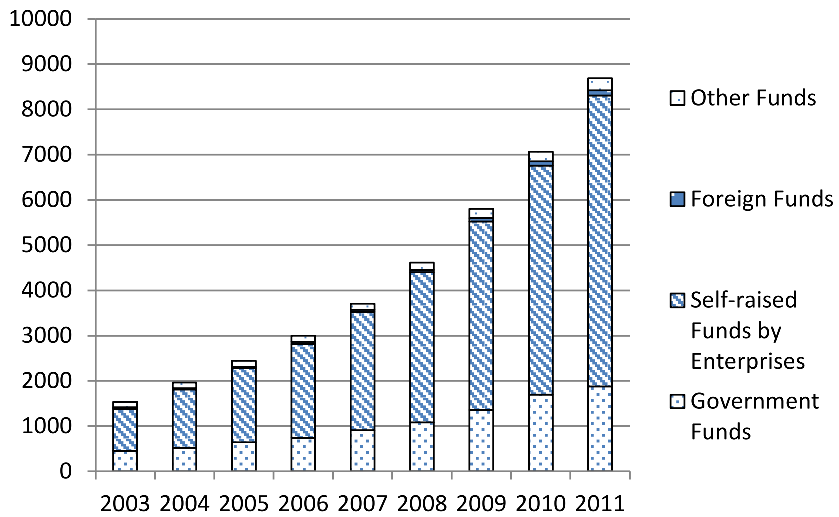
Figure 2. Gross domestic R&D expenditure by major countries
(Million USD, 2005 constant prices and PPPs)



Source: OECD iLibrary(http://www.oecd-ilibrary.org/).

The major actor of China's R&D expense, however, is the firm, not the government, as clearly shown in Figure 3. The firms' self-raised internal funds accounted for 73.9% of total R&D expenditure in 2011, while the government accounted for 21.7%. Therefore, to achieve the MLPST target, it is necessary to stimulate the R&D of firms. Thus, the Chinese government has implemented various large subsidies and incentives for R&D activities, including tax deductions for high-tech certified firms, incentives to invite talent, and equipment depreciation.[4]

Figure 3. China's R&D Expenditure by Source
(100 million RMB)



Source: *China Statistical Yearbook on Science and Technology*, 2012, p. 11.

[4] For more detail, see the original MLPST document.

Another key feature of Chinese innovation policy is the "multi-level and multi-route" initiatives. According to MLPST and related policy documents, the Chinese national government places particular emphasis on the role of each government level and policy agency; namely, the horizontal and vertical government agencies and initiatives (Figure 4).[5]

First, the "multi-level" policy initiative means the horizontal government initiatives, including the national-, provincial-, and city-level programs. At the highest level, the State Council Steering Group of S&T and Education coordinates the policy generation process. Similar mechanisms for promoting the innovation of local firms exist in the lower levels of government, especially the provincial and municipal governments. Consequently, a firm or research institute has numerous options when applying for policy support. During the 2006–2008 period, 79 innovation policies were issued by various ministries, which were also implemented at the lower levels. For instance, as we describe later, the "innovation policy for highly educated talent" was implemented by national-, provincial-, and some city-level governments.[6] In addition, we note that the total amount of S&T–related expenditure by local governments is the same as that spent by the national government (as mentioned earlier). Therefore, the role of local government is also essential when examining the Chinese S&T and innovation policies.

Second, the "multi-route" policy is characterized by various vertical agencies. The Ministry of Science and Technology (MOST), National Development and Reform Commission (NDRC), Ministry of Finance (MOF), and Ministry of Education (MOE) play important roles in this vertical structure. According to Liu et al. (2011), MOST was involved in 42.3% of innovation policy between 1985 and 2005, and played a dominant role among innovation policymakers. During the 2006–2008 period; namely, after the introduction of MLPST, MOF replaced MOST with a 46.8% participation rate in terms of innovation policy. Other ministries and agencies, such as the Ministry of Industry and Information Technology (MIIT), Ministry of Education (MOE), and Chinese Academy of Sciences (CAS), are also involved in policymaking. Although Liu et al. (2011) show that these other agencies only play a minor role in innovation policy, in terms of other indicators such as the fund for State Key Laboratories imply their relative importance.[7] Due to its obvious importance, we pay particular attention to the policy programs undertaken by MOST.

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5 In chapter 9 of MLPST, the establishment of multilayer and multi-route science and technology policies has been mentioned as one of the mid-term and long-term policy goals. In related policy documents, several similar usages appear; namely, "multi-dimensional and multi-route (*Duo Cengci, Duo Suidao*)" and "multilayered and multi-route (*Duo Yuanhua, Duo Suidao*)." To check the detail of these contexts, see Chen (2006, pp. 31–32, p. 38, p. 40, and pp. 61–62).

6 Compared with the cases of Central American countries presented in Padilla-Péreza and Gaudin (2014), China has more comprehensive agency frameworks and financing policies, including R&D incentives.

7 Although Liu et al. (2011) show that MIIT, MOE, and CAS were only involved in a limited number of policies compared to MLPST, the State Key Laboratories statistics show large R&D inputs by MOE and CAS, in particular. Hence, the importance of agencies should be evaluated using many sources and projections.

Figure 4. Major Chinese government agencies for S&T and innovation policies

	MOST	NDRC	MOF	MIIT	MOE	CAS
Main policy target	Technological development	Resource allocation and macroeconomic management	Fiscal support for strategic industry and technology	Industrial development	Human resource development	Scientific research
Central level	Ministry	Ministry	Ministry	Ministry	Ministry	Institutes
	↓	↓	↓	↓	↓	
Provincial level	Bureau	Bureau	Bureau	Bureau	Bureau	
	↓	↓	↓	↓	↓	
City level	Section	Section	Section	Section	Section	

Source: OECD(2009), Liu, et al (2011), and author's field interviews.

2.3 Case of Chengdu, an inland city

To arrive at a deeper understanding of Chinese innovation policy menus and procedures, and their treatment effects, the remainder of this paper focuses on the case study of Chengdu, an inland city. Chengdu is a provincial capital, with a population exceeding one million people, in the Western region of China, and holds a sub-provincial administrative status. The major cities in the Western region are aggressively promoting high-tech industries with the support of national government planning, such as the *Western Development Plan* (西部大开发). Therefore, it is valuable to evaluate the S&T policy effects using the data from this city.

Table 1 presents the support initiatives and subsidies for S&T projects that were offered to firms and institutions in the city. In 2012, firms and institutions in Chengdu benefited from 299 national programs, 509 provincial programs, and 928 city programs (1,736 S&T programs in total, amounting to 591.8 million yuan). As the table indicates, upper-level programs tend to offer larger average subsidies; however, national-, provincial-, and city-level projects provide a similar amount of funds.

Table 1. Support for S&T development in Chengdu (2008–2012)

	National project			Provincial project			City project		
Year	Number of project	Supported amount (million yuan)	Avarage support (million yuan)	Number of project	Supported amount (million yuan)	Avarage support (million yuan)	Number of project	Supported amount (million yuan)	Avarage support (million yuan)
2008	152	771	5.07	267	40	0.15	N.A.	N.A.	N.A.
2009	239	377	1.58	374	78	0.21	N.A.	N.A.	N.A.
2010	215	373	1.73	327	111	0.34	N.A.	N.A.	N.A.
2011	193	243	1.26	480	174	0.36	N.A.	N.A.	N.A.
2012	299	208	0.70	509	216	0.42	928	167.8	0.18
Total	1098	1972	1.80	2103	660	0.31	N.A.	N.A.	N.A.

Source: Annual Report of the National Innovative City Construction of the researched city.

Based on a government survey data for the city, we identified five categories and 27 individual S&T and innovation policies that benefited the local firms and institutions, as shown in Table 2. The first category, (A) Policy on Innovation Service Systems (创新服务体系类 in Chinese), includes six programs to promote equipment sharing and information exchange support. Inspection equipment sharing (大型仪器共享), consulting on technological strategy (科技咨询服务), and three other programs were implemented in 2007. The second category, (B) Service for intellectual property rights (IPR) and commercialization (成果转化类), comprises five incentives. Typical benefits associated with this category include administrative support and subsidies for IPR registrations (专利资助). The third category, (C) Policy certification for high-tech firms includes four preferential programs, such as "high-tech certification (高新技术企业认定)." In fact, these certification policies are well-known in China and income tax is deducted from 25% to 15% in maximum. The fourth category, (D) Financial support and Tax incentives, involves incentives, such as tax deductions for R&D expenses (研发费用税前扣除) and key software firms (重点软件企业税收优惠). The fifth category, (E) Talent preferential policies, comprises national-, provincial-, and city-level programs for human resources, including subsidies for hiring overseas talent (千人计划, 百人计划).[8]

[8] Since there are many policies, the Chinese firms often display several awards or policy certifications from different levels of government.

Table 2. List of S&T policies in Chengdu

	Policy Category	Name of Policy Program	Starting Year
1	(A) Policy on Innovation Service System	Large gauge equipment sharing	2007
2		Technology information and intelligence sharing	2007
3		Technology strategic decisions consulting	2007
4		Agricultural S&T innovation service platform	2007
5		S&T achievements service	2007
6		Major industrial technology platform	2010
7	(B) Service for IPR and Commercialization	Technology contract registration	2000
8		Subsidy for IPR registration	2005
9		S&T incentive	2006
10		Integrated services for Intellectual property	2007
11		Technology trading subsidies	2013
12	(C) Policy Certification for High-tech Firm	Support for high-tech certificated firm	1996
13		Provincial certification as innovative enterprises	2007
14		City certification as independent innovation products	2007
15		certificated as technically advanced service enterprises	2010
16	(D) Financial support and Tax incentives	Tax incentives for key software enterprise	2000
17		Tax incentives of equity investments in venture capital enterprises	2006
18		Tax deduction of R&D cost	2008
19		Technology insurance	2008
20		Counseling programs for Tech-SMEs to list	2010
21		Tax incentives for enterprise who undertake national S&T major project	2010
22		Seed capital	2011
23		Risk compensation fund	2011
24		Tax incentives for nonprofit SME credit guarantee	2012
25	(E) Talent preferential policies	National "Thousand Talents Program"	2008
26		Provincial "Hundred Talents Program"	2009
27		City-level high creative talent preferences	2011

Source: City Government Survey.

The typical procedure for participating in the programs established by these policies is as follows: submission of an application, screening, evaluation, and final selection. For example, in the case of the city's talent policy, the policy-selection procedure comprises four steps, which include submission through final selection (see Table 3). As a first step, the firm or research institute submits a proposal to the industrial park. In the second step, the city government establishes a special office and committee for this selection procedure. Finally, the selected firm gains one million RMB worth of subsidies and other preferential services from the city government. This procedure clearly suggests that the city government selects its target firms based on the firm proposals; no evaluation and feedback mechanism exists after implementation of the subsidies.

Table 3. Chengdu's policy procedure (case of Talent support)

Required condition of talents	High-level innovative talent who generally has a Ph.D. degree, younger than 56 years old, and will work at the city at least 6 months after the certification.
	High-level entrepreneurial talent who generally has a oversea degree or Master degree, younger than 56 years old, and will work at the city at least 6 months after the certification.
Procedure of policy	(1)Submit. Firms or institutions submit a proposal to Industrial Park, and each Industrial Park submits these proposals to Department of Organization at located district or county.
	(2)First screening. Each department of organization report to the City Special Office(CSO). Regarding Innovative talent, Department of Science and Technology examines as the first step. Regarding Entrepreneurial talent, Department of Human-resource and Society examines as the first step. The CSO recommends candidates based on the opinions of each department.
	(3)Investigation and recommendation. The CSO establishes specialists committee, and the committee makes a list of candidates. The list is sent to the City Human-resource Leading Small Group.
	(4)Judgment. The City Human-resource Leading Small Group finalizes the list.
Details of support (abstract)	(1)City government establishes a special fund, which is 120 million yuan in 2011. The amount of budget changes with the increase rate of total fiscal income in each year.
	(2)The fund supports 1 million yuan for each talent. Those who are listed in National Thousand Project and Provincial Hundred Project will be directly supported.
	(3)Firms or institutions and the local government also support the talent to improve the working conditions.
	(4)If the talent starts a project that has strategic importance for the city, city government supports at least 1 million yuan and a 100 square meters working place for 3 years.

Source: The City government's document.

It is worth noting that the 27 firm-level policies listed in Table 2 generally attempt to reduce the firm-level R&D costs by shifting the MCC schedule to the right, as shown in Figure 1. Simultaneously, each policy category has its own detailed target. For example, (A) enhances information sharing and equipment sharing, which have no specific target indicator. On the other hand, (B) is clearly targeting an increase in IPR registrations by firms. The third to fifth categories, (C), (D), and (E), do not specify the principle target outputs. Another issue is that several ministries are involved in the policy-making process. It is noteworthy that categories (A), (B), and (C) are mainly proposed by MOST's initiatives, while (D) is overseen by the MOF, and (E) is the responsibility of the MOE. Meanwhile, estimating the policy-treatment effects by category allows us to evaluate the effectiveness of the major ministry policies.

3. Method and Data

3.1 Method

In following sections, we estimate an econometric model to investigate the policy treatment effects. One possible strategy, to estimate the policy effects, is shown below as follows:

$$Y_i = a + \sum_{k=1}^{q} x_{ik}\, \beta_k + \gamma Policy_i + u_i \quad (1),$$

where Y_i, the dependent variable, is firm *i*'s output value or number of innovation activities, such as number of new IPR, new products, and process improvements. Independent variables include firm inputs and several control variables. A firm's individual characteristics (x_{ik}) may represent the number of workers, percentage of R&D staff, an ownership dummy (state owned, foreign investment, or joint venture), and firm age (and its square).[9] u_i is the error term.

Our central interest is the treatment effect of γ on our innovation proxy variables. To investigate the policy treatment effects using equation (1), the endogeneity issue arises. Again, our central interest is how much and what types of policy stimulate the firms' innovation activities; however, policymakers may tend to choose a "better performing firm" as their policy target. In other words, the unobserved firm capability variable A_i could have a correlation with $Policy_i$. Consequently, the coefficient of simple regression estimations contains both the treatment effect (in this case, the policy effect) and selection effect, resulting in an overestimation bias.

To avoid this selection effect, we employ the propensity score matching (PSM) method. The PSM is a non-parametric (or semi-parametric) statistical approach that eliminates potential selection bias in non-experimental settings and it is used in a wide range of recent policy evaluation studies (Lee, 2005). The PSM employs predicted probabilities of treatment (in this case, policy treatment) based on a probability model; typically, the logit or probit model, and obtains the propensity score for each observation. Using this score, each treatment observation is matched with a control observation or group that has a "similar" pretreatment condition to estimate the causal effect.

A basic method of the PSM is as follows (Dehejia and Wahba, 2002; González and Pazó, 2008). Let T_i be a dummy variable that takes the value of one if firm *i* receives a subsidy. Let $Y_i(0)$ be the innovation activities of firm *i* in the case of no subsidies and let $Y_i(1)$ be the innovation activities of firm *i* in the case of subsidies. The treatment effect of subsidies is $Y_i(1)$–

[9] Motohashi and Yun (2007) show that Chinese firms are increasingly outsourcing R&D activities. It is valuable to estimate the university–industry cooperation effect; however, this paper focuses on the effect of policies.

$Y_i(0)$ (γ in equation (1) under the assumption of random treatments; in other words, experimental settings). Since $Y_i(1)$ and $Y_i(0)$ are not simultaneously observable, we need to obtain estimates of $Y_i(0)$ counterfactually. The PSM method assumes that, if pretreatment characteristics $\boldsymbol{X}_i$ are similar (or exactly the same), the treatment effects are observable by comparing the treated firm *i* and the non-treated firm *j*. The underlying two assumptions of PSM are as follows:

$$\mathrm{E}[\mathrm{Y}(0)|\mathrm{T}=1, \mathrm{X}=\mathrm{x}] = \mathrm{E}[\mathrm{Y}(0)|\mathrm{T}=0,\ \mathrm{X}=\mathrm{x}],$$

and

$$\mathrm{E}[\mathrm{Y}(1)|\mathrm{T}=1, \mathrm{X}=\mathrm{x}] = \mathrm{E}[\mathrm{Y}(1)|\mathrm{T}=0,\ \mathrm{X}=\mathrm{x}]. \quad (2)$$

The first assumption is called the *unconfoundedness* assumption, implying the pair is twin under the same pretreatment condition. Under this assumption, we can estimate the treatment effect $Y_i(1)$ - $Y_i(0)$ by $\mathrm{E}[\mathrm{Y}(1)|\mathrm{T}=1, \mathrm{X}=\mathrm{x}]$ - $\mathrm{E}[\mathrm{Y}(0)|\mathrm{T}=0,\ \mathrm{X}=\mathrm{x}]$. To match the treatment observation with “similar” precondition control observations, the second assumption; namely, the *Overlap* assumption, $c<(T=1|X=x)<1-c$, arises (here $1>c>0$). We use the probability estimator to find a sample with the nearest or most similar characteristics (for more details of the matching process, see Dehejia and Wahba, 2002). After matching, our measurement of any treatment effect is the average treatment effect on the treated firms (ATT), calculated by the weighting scheme below as follows:

$$\mathrm{ATT} = \frac{1}{N}\sum_{i|T_i=1}[Y_i(1) - \frac{1}{J_i}Y_j(0)], \quad (3)$$

where *N* is the number of the treatment observations (number of firms with policy support) and J_i is the set of comparison units matched to treatment unit *i;* if one comparison unit is matched, then $J_i = 1$.

For instance, Almus and Czarnitzki (2003) used survey data to evaluate the treatment effect of R&D subsidies in eastern Germany. They estimated the probability of treatment, using a probit model with various items of firm information, including the number of employees (and its square), an industry dummy, an R&D department dummy, and capital intensity. Their results suggest that subsidies stimulate R&D intensity by 3.94%.

Our empirical strategy is as follows. First, we estimate the probability of treatment by the probit model. Then, using the obtained score, we match the treatment firms with the control group and estimate the policy treatment effect. Particularly, the $\boldsymbol{X}_i$ variables in the probit estimation that represent the number of workers are replaced by the registered capital variables to capture the pretreatment characteristics. All control observations for each policy are chosen within the limitations of caliper 0.01 of the baseline propensity score.[10]

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[10] As Dehejia and Wahba (2002) discussed, caliper matching allows extra units of estimation that reduce the bias at the cost of precision. In our dataset, as reported in our appendix figures, some policy treatment observations are relatively scarce, although the distributions obviously overlap. To fully use the control sample to reduce any bias, we employ the caliper approach (caliper = 0.01) for our matching procedures.

For our first step, the entire range of policy-targeted firms (namely, firms benefitting from any one of the policies implemented before 2009, as shown in Table 2) is given a dummy variable of 1, while non-targeted firms are given a dummy variable of 0. This estimation shows whether S&T-related policies as a whole stimulate firm activities. As discussed in Section 2, the Chinese innovation system obviously has both horizontal and vertical agencies and initiatives. To investigate both effects, we conduct a PSM estimation using both horizontal and vertical policies after estimating the total policy treatment effect. A firm often benefits from the numerous S&T policies from different levels of government, so it is informative to estimate the treatment effects of each national-, provincial-, and city-level policy. The vertical policy–category estimations clarify what types of policy are effective.

Our analytical hypotheses are explained below. First, as shown in Table 1, the higher government agencies provide larger funds, on average. However, they generally have limited capacity to screen the firm-level information due to the vast geographical and socio-political distances in a developing country like China. Therefore, we can assume that the efficacy of policy levels depends on the average budget scale and information capacity of each government level. Since the information capacity of each government level is not observable, we do not present a specific hypothesis on the policy efficacy of each government level. Second, as for the policy categories, innovation services and commercialization support policies attempt to stimulate innovation activities, which allow us to assume a positive treatment effect on the number of IPRs, new products, and process improvements, but not on output. On the other hand, certification and talent policies do not target specific indicators; however, these two policies also attempt to promote the firms' activities overall. Hence, we also hypothesize a general positive treatment effect.

Although our estimation strategy can evaluate the treatment effect, it also has a limitation. Our research method focuses on the private- and internal-firm effects of each policy, which can be observed by comparing the treatment and control groups. In other words, if policy stimulates the innovation activities of firms in the same region and, simultaneously, the control group through the spillover effect, our estimation strategy cannot observe such external effects.

3.2 Data

Our dataset has several advantages and a limitation. Its first advantage is that it has nearly 400 observations collected by the city government agency in 2012 that include both the manufacturing and service industries, such as the software industry. Since Chinese data on the service industry are scarce, our results indicate a more comprehensive effect on innovation activities. Its second advantage is the fact that it contains detailed information on more than 20 individual policies and using this information, we can investigate the treatment effects by policy level and category. A third advantage is that our dataset contains three innovation proxies; namely, number of IPRs, new products, and process improvements that allow evaluations by several measurements.

Simultaneously, the survey that collected the data was not entirely well-designed. The main data problem is that the major variables were generally collected from 2011 data, with the exception of the total number of IPRs, new products, and process improvements between 2010 and 2012. Due to this data issue, we can only obtain a three-year average of innovation proxies by dividing the innovation variables by three. Although each policy information datum lacks a precise starting year for the subsidies or support at the individual firm-level, the majority of policies had started before 2010; in particular, after the introduction of MLPST, so we can assume that the policies implemented up to 2009 should have causal impacts on the innovation proxies. We use policy variables which implemented till 2009, otherwise dropped.

Table 4 summarizes the descriptive statistics. As shown, the policy-targeted firms are generally larger than the non-targeted firms in terms of number of employees and registered capital; they also produce more IPRs and new products. All of these factors suggest a selection effect.[11] The policy treatment firms (entire policy dummy = 1) report approximately 2.6 IPRs, 5.4 new products, and 3.2 process improvements, while the numbers for the non-targeted firms are only 0.4, 1.2, and 0.8, respectively. Table 5 reports the probit estimation results for the entire policy treatment using only the pretreatment control variables, such as the log of registered capital, the SOE and FDI dummies, the core-district and high-tech-industry dummies, and firm age, showing reasonable coefficients for the control variables.[12] The larger firms in terms of registered capital, state-owned enterprises (SOEs), firms located in the central districts, and firms having certain characteristics (positive for age, negative for the square of age) are likely to be selected by various government policies. Probit results for each policy level and category are shown in the Appendix, Table 1.

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11 As for the national-, provincial-, and city-level policies, a small portion of firms is non-zero, given that the entire policy dummy = 0. This is because the questionnaire asks for each level of government policy as an independent section. Since these proportions are quite low (e.g., 0.055 for the national-level under the condition that the entire policy dummy = 0), we use these original categories for our calculations.

12 Since the ratio of R&D workers, R&D department dummies, and industry–university collaboration dummies may be latent variables that are influenced by the treatments, we use only variables that are basically not influenced by the policy implementations in our baseline case.

Table 4. Descriptive statistics by policy-target dummy

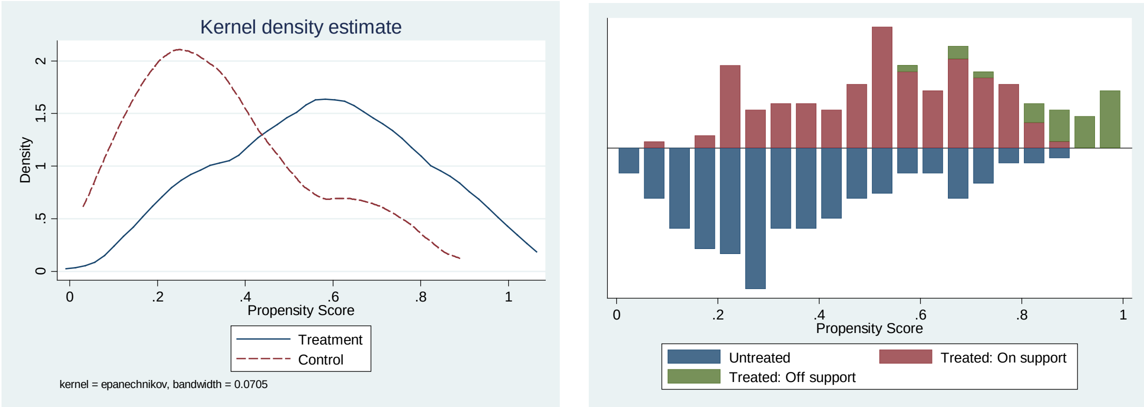
	Full sample		Entire policy dummy = 1		Entire policy dummy = 0	
Variable	Observation	Mean	Observation	Mean	Observation	Mean
Output	360	6931.342	159	13822.810	201	1479.881
IPR	394	1.442	177	2.676	217	0.435
New product	394	3.134	177	5.467	217	1.230
Process improvement	393	1.905	176	3.259	217	0.806
Employee	394	153.893	177	257.627	217	69.281
log(Registered capital)	391	5.902	176	6.650	215	5.290
Ratio of R&D worker	394	0.232	177	0.260	217	0.210
R&D department dummy	394	0.622	177	0.819	217	0.461
Industry-university collaboration dummy	394	0.500	177	0.627	217	0.396
SOE dummy	394	0.069	177	0.124	217	0.023
FDI and joint venture dummy	394	0.135	177	0.186	217	0.092
Core district dummy	394	0.398	177	0.463	217	0.346
High-tech industry dummy	394	0.541	177	0.610	217	0.484
Age of firm	392	6.339	176	8.011	216	4.977
Sqare of age	392	73.217	176	100.330	216	51.125
Entire policy	394	0.449	177	1.000	217	0
National policy	394	0.155	177	0.277	217	0.055
Provincial policy	394	0.228	177	0.446	217	0.051
City policy	394	0.289	177	0.554	217	0.074
Service policy	394	0.183	177	0.407	217	0
Commercialization policy	394	0.259	177	0.576	217	0
Certification policy	394	0.236	177	0.525	217	0
Tax incentive	394	0.201	177	0.446	217	0
Talent policy	394	0.028	177	0.062	217	0

Table 5. Probit estimation results for the entire policy treatment

	Coefficient	Z statistics
Log(registered capital)	0.226	5.08
SOE dummy	0.859	2.48
FDI and Joint venture dummy	0.350	1.74
Core district dummy	0.457	3.01
hightech industry dummy	0.176	1.18
Age of firm	0.106	3.51
Square of Age	−0.003	−2.36
Constant	−2.320	−7.89
Observation	390	
Log Likelihood	−219.59306	
LR chi2(7)	97.76	
Prob>chi2	0.0000	
Pseudo R2	0.1821	

Using the probit estimation results, we match the treatment firm with the control group having a similar probability of being chosen in terms of a particular government policy. Figures 5-a and 5-b report the pre-matching distribution and matching situation. The PSM requires overlapping propensity scores for the treatment and control groups, and Figure 5-a shows a clear overlap of the treatment- and control-group distributions.

Figures 5-a and 5-b. Propensity scores of the entire policy treatments and their matching results



Note: Average bias of matching is 4.3%, and 26 of 158 treatment observations are off support due to the criterion (caliper = 0.01).

4. Estimation Results

4.1 Do these policies improve firm performance?

Table 6 reports the results of the entire policy estimation. Our central interest is ATT, which is the average treatment effect on the treated observations calculated by equation (3). Our results indicate that the difference of the unmatched data contains a relatively large selection effect. In the case of IPR, the difference between the treated and control groups of unmatched data is 2.35, while the matched comparison reports 1.97 with statistical significance at the 1% level (T statistics is 4.26), suggesting that the policy as a whole stimulates the number of IPRs by 1.97. A certain selection effect can also be seen in the cases of new products and process improvements, especially the latter.

Table 6. Treatment effects of the entire policy

Variable	Output		IPR		New product		Process improvement	
Sample	Unmatched	ATT	Unmatched	ATT	Unmatched	ATT	Unmatched	ATT
Treated	13593.21	5733.78	2.81	2.54	6.02	5.44	3.61	2.88
Controls	1469.28	1500.81	0.46	0.56	1.30	1.59	0.86	1.38
Difference	12123.93	4232.97	2.35	1.97	4.72	3.85	2.75	1.50
S.E.	3287.15	1291.39	0.39	0.46	1.22	1.45	0.67	0.54
T-stat	3.69	3.28	5.95	4.26	3.87	2.66	4.12	2.80

4.2 Which level of policy is effective?

Our next step focuses on the horizontal structure of innovation policy. The results are shown in Table 7 and suggest that lower levels of government are more effective in implementing S&T policies. The city-level policies have positive and significant impacts on all four output variables. In contrast, the national policy report shows mixed results; a negative impact on output without any statistical significance and a positive effect on IPR without any statistical significance, as well. The policies of provincial-level governments (i.e., the mid-level between the national and city government policies) have generally positive and significant treatment effects, with the exception of the impact on the number of new products.

Table 7. Treatment effects of the horizontal policy

		Output		IPR		New product		Improvement	
		Unmatched	ATT	Unmatched	ATT	Unmatched	ATT	Unmatched	ATT
National	Difference	7982.87	−6683.80	2.55	1.35	3.53	0.90	3.16	0.93
	T-stat	1.79	−0.50	4.75	1.70	2.13	0.30	3.51	0.77
Provincial	Difference	16107.06	7425.38	3.40	3.29	4.07	1.50	3.94	4.20
	T-stat	4.22	2.57	7.60	4.11	2.83	0.53	5.11	2.86
City	Difference	14094.90	5060.89	3.21	2.67	4.19	4.76	3.79	3.09
	T-stat	3.95	2.17	7.69	4.56	3.14	2.62	5.29	3.41

In addition, we can calculate the average unit cost to stimulate one IPR or another output variable using the data in Table 1. Due to inadequate stimulation effects for new products and process improvements at the national level, we could only calculate the case of IPR. As shown in Table 1, the average cost of national-, provincial-, and city-level projects in 2012 is 0.70 million RMB, 0.42 million RMB, and 0.18 million RMB, respectively. Dividing these costs by the estimated magnitude of each policy level, the average cost per IPR at the national-, provincial-, and city-levels is 0.51 million RMB, 0.12 million RMB, and 0.06 million RMB, respectively. These results imply that the policies implemented by the lower levels of government are more effective and efficient.

4.3 What types of policies are effective?

Table 8 presents the results of the vertical policy structure, suggesting positive and significant treatment effects of the service, certification, and talent policies. Taking service policy as an example, the treatment effect for IPR is 2.35 with high statistical significance. This means that the entire service policy stimulates the firm’s IPR production by 2.35. Another effective policy is commercialization, which stimulates 1.9 IPRs per treatment, on average, as well as other innovation proxies. It is noteworthy that financial and tax incentives, and talent policy, have a generally weak impact on output and innovation activities. As discussed in Section 2, the policy categories reflect the vertical structure of China’s policy system and these results address the effectiveness of policy initiatives by MOST. However, evaluating the effects according to these results is difficult because only a few firms benefited from the talent policy (see Table 4).

Table 8. Treatment effects of the vertical policy

		Output		IPR		New		Process	
		Un-matched	ATT	Un-matched	ATT	Un-matched	ATT	Un-matched	ATT
(A) service policy	Difference	12841.48	-356.39	2.43	2.35	6.33	6.76	1.61	2.15
	T-stat	3.05	-0.10	4.76	2.58	4.09	2.22	1.86	1.89
(B) commercialization support	Difference	15454.18	3552.41	3.19	1.90	4.88	4.24	3.75	2.52
	T-stat	4.22	1.46	7.39	2.56	3.56	2.50	5.06	3.68
(C) certification policy	Difference	17847.02	6992.13	3.77	3.11	2.98	2.80	3.24	1.71
	T-stat	4.69	2.74	8.54	3.82	2.05	1.18	4.14	1.22
(D) financial and tax incentive	Difference	16341.64	2071.31	1.87	-0.01	6.11	5.55	2.68	1.69
	T-stat	4.07	0.67	3.76	-0.01	4.10	1.60	3.25	1.48
(E) talent policy	Difference	8336.81	10619.30	-0.31	0.63	9.38	12.13	0.06	1.50
	T-stat	0.83	1.32	-0.25	1.11	2.52	1.25	0.03	1.60

4.4 Robustness Check

To assess the robustness of our results, we conducted three additional estimations. First, we used a different matching method—nearest-neighbor matching—to check for robustness. The results are shown in the Appendix, Table 2. This modification of the matching method does not change our basic findings, as stated in the previous section.

Second, we conducted stricter probit estimations by using exact matching of industry or firm ownership. To exactly match the treatment firm and control group by industry or ownership, a larger sample size or a more substantial overlap of propensity scores is required. Due to these inadequate conditions, we can check the entire policy estimation by exact matching in our dataset. In terms of industry exact matching, the policy stimulation effects are 2.10 for IPR, 4.72 for new products, and 2.06 for process improvements, and in terms of ownership exact matching, the effects are 2.00 for IPR, 3.76 for new products, and 2.07 for process improvements. In addition, we conducted probit models with dummy variables for other policy acceptances to control for the effect of other policies. The results are shown in the Appendix, Table 3 and the main findings are as follows: national- and provincial-level policies have no significant stimulation effects, while city programs have positive and significant effects on three innovation proxies; as for the policy categories, tax and financial subsidies have no positive impacts, while categories (A) and (C) have at least one positive and a significant effect on the innovation proxies.[13]

Third, the ordinary least square (OLS) estimation results are presented in the Appendix, Tables 4 to 6, and they suggest similar policy effects, with the exception of positive and significant treatment effects of financial and tax policies on output.[14] According to these modifications of the estimation models, our baseline results remain generally consistent.

[13] We also checked the results by adding the R&D department dummy, industry–university collaboration dummy, and number of employees to the probit model. According to Almus and Czarnitzki (2003), S&T policy does not typically aim to increase the number of R&D workers, problem using these variables as covariates is limited. Our results suggest that, even though the magnitude of the policy effect becomes smaller, the basic result and findings do not change.

[14] Even though the OLS estimations with the control variables often include both the treatment and selection effects, the results are consistent with our PSM baseline case.

4.5 Discussion

A series of causal estimation results presents that policies implemented by lower levels of government as well as services for boosting innovation activities are both positively and statistically significant in stimulating firm-level innovation activities. Physical supports (e.g., inspection equipment–sharing) and commercialization policy play a clear positive role, while the financial and tax incentive treatment effects do not stimulate innovation activities. Although no negative and significant effects are observed in our calculations, it is also worthwhile to note that several channels of innovation policy have no positive treatment effects. This implies that the current Chinese policy menu is not completely effective and there is room to restructure the innovation systems and procedures.

5. Conclusion

In this paper, we investigate the firm-level treatment effect of S&T policies in China by using detailed policy information. At the beginning of this paper, we raised our central research question: what types of policies are more effective? This question is essential when evaluating the Chinese innovation initiative, which is characterized as a "multi-level and multi-route" system. Recent papers on policy evaluation often use the propensity score matching approach to eliminate selection bias in non-experimental settings (Almus and Czarnitzki, 2003; González and Pazó, 2008). Accordingly, we employ this approach in the case of China. Our contribution is that we show the treatment effects by S&T policy level and category. Our results suggest that positive and significant treatment effects exist for three innovation proxies; in other words, such policies stimulate innovation activities. As discussed in Section 4, the entire range of S&T policies increases a firm's IPR production by a factor of 1.97. Despite the fact that Chinese national and local governments have relatively little experience in implementing innovation policies with market mechanism and conducting numerous trial policies, our results present data on the effectiveness of government subsidies and services. The answer to our central question is that certification, commercialization policy, and policies undertaken by lower levels of government are more effective than other policies, whereas the treatment impact of tax incentives and national-level policies is statistically insignificant.

Our results imply several policy implications, especially in terms of the level and category estimations. Both the national and local governments in China are aggressively engaging in S&T and R&D promotion; however, the effectiveness of these policies varies. In other words, the "multi-level and multi-route" system of innovation policies has a room to improve and restructure. To improve the efficiency of the substantial S&T fiscal expenses, it would be beneficial to restructure the policy framework. Some policies (e.g., financial and tax policy) may result in moral hazard or opportunistic behavior, which means that the subsidized firms do not, in practice, conduct innovation activities.[15] Finally, inadequate evaluation and feedback mechanisms for each policy are critical weakness that needs to be addressed. González and Pazó (2008) mentioned the inadequate evaluating programs, even in the OECD countries. Moreover, it is also a global issue. OECD (2009) has already warned us about this issue in China and it has recommended that further policy evaluation studies and government feedback regarding their actions are beneficial in fostering innovation.

Although our results indicate that some policy channels are presently ineffective, we do not overstate the limitations of the policy effects. Our method only evaluates the private and internal-firm effects. Hence, our results do not reject the possibility of positive treatment effects, along with strong spillover effects among firms in a region. Accordingly, our findings in terms of policy level may only suggest that the policies in Chengdu, our research city, are well-organized and designed, and that such policies do not imply that the performance of lower-level government policies are always better than that of higher-level government policies. An evaluation using different regions and datasets would be required to obtain a more comprehensive and robust suggestions.

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[15] Steinmueller (2010) mentions that subsidy policies may suffer from the opportunistic behavior of firms. During our field interviews in the city, some local government-related officers and managers of private firms noticed that some firms were trying to gain government S&T support and subsidies for their survival. One reason for this is that the subsidy size is too large compared with the sales volume of the average small and medium enterprises; for example, one million RMB in the case of the talent support program. These subsidies may do not stimulate innovation activities; instead, they would be used for ordinary management expense.

Appendix

Table A.1. Probit results by policy level and category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	National policy	Provincial policy	City policy	Service for innovation	Commercialization program	Certification policy	Tax incentive	Talent policy
Log(registered capital)	0.153***	0.198***	0.256***	0.206***	0.227***	0.226***	0.161***	0.132
	(0.0543)	(0.0510)	(0.0479)	(0.0495)	(0.0491)	(0.0499)	(0.0494)	(0.0852)
SOE dummy	0.542*	0.363	0.527*	0.565**	0.413	0.396	0.673**	0.0360
	(0.293)	(0.289)	(0.291)	(0.280)	(0.296)	(0.294)	(0.285)	(0.522)
FDI and Joint venture dummy	0.307	0.344	0.241	0.243	0.130	0.274	0.310	0.563*
	(0.226)	(0.211)	(0.201)	(0.214)	(0.206)	(0.210)	(0.212)	(0.329)
Core district dummy	0.166	0.273	0.179	0.0726	0.152	0.225	0.246	0.0664
	(0.179)	(0.168)	(0.159)	(0.166)	(0.161)	(0.167)	(0.169)	(0.298)
hightech industry dummy	0.256	0.283*	0.229	0.157	0.363**	0.274*	0.159	−0.156
	(0.181)	(0.169)	(0.158)	(0.166)	(0.160)	(0.166)	(0.167)	(0.296)
Age of firm	0.200***	0.238***	0.0810**	−0.0313	0.0911***	0.153***	0.0804**	−0.00118
	(0.0571)	(0.0524)	(0.0318)	(0.0331)	(0.0323)	(0.0378)	(0.0329)	(0.0632)
Square of Age	0.00839***	0.00962**	−0.00192	0.00109	−0.00199	0.00509**	−0.00169	−0.000251
	(0.00289)	(0.00264)	(0.00121)	(0.00125)	(0.00123)	(0.00160)	(0.00123)	(0.00265)
Constant	−3.056***	−3.263***	−2.815***	−2.264***	−2.835***	−3.114***	−2.558***	−2.784***
	(0.402)	(0.377)	(0.327)	(0.327)	(0.336)	(0.352)	(0.336)	(0.581)
Observations	390	390	390	390	390	390	390	390
Pseudo R square	0.1592	0.2026	0.1751	0.0955	0.1686	0.1893	0.1399	0.0678

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1 respectively.

Table A.2. Robustness check using nearest-neighbor matching

		output		newipr		new product		improvement	
		Un-matched	ATT	Un-matched	ATT	Un-matched	ATT	Un-matched	ATT
entire	Difference	12124	11660	2.35	2.30	4.72	4.61	2.75	2.41
	T-stat	3.69	3.11	5.95	5.09	3.87	3.02	4.12	2.99
national	Difference	7983	−19124	2.55	2.01	3.53	−1.72	3.16	1.25
	T-stat	1.79	−1.50	4.75	2.18	2.13	−0.41	3.51	0.55
provincial	Difference	16107	14385	3.40	3.54	4.07	2.04	3.94	3.98
	T-stat	4.22	2.20	7.60	4.72	2.83	0.73	5.11	2.99
city	Difference	14095	11480	3.21	3.17	4.19	4.51	3.79	3.61
	T-stat	3.95	2.16	7.69	5.14	3.14	2.72	5.29	3.25
(A) service policy	Difference	12841	6168	2.43	1.72	6.33	6.02	1.61	0.77
	T-stat	3.05	0.71	4.76	1.56	4.09	2.04	1.86	0.37
(B) commercialization support	Difference	15454	12408	3.19	2.54	4.88	5.42	3.75	3.95
	T-stat	4.22	2.12	7.39	3.16	3.56	2.76	5.06	3.28
(C) certification policy	Difference	17847	9648	3.77	3.52	2.98	2.63	3.24	2.47
	T-stat	4.69	1.22	8.54	4.42	2.05	1.20	4.14	1.50
(D) financial and tax incentive	Difference	16342	11578	1.87	0.45	6.11	4.46	2.68	2.34
	T-stat	4.07	1.43	3.76	0.35	4.10	1.41	3.25	1.57
(E) talent policy	Difference	8337	10619	−0.31	0.63	9.38	12.13	0.06	1.50
	T-stat	0.83	1.32	−0.25	1.11	2.52	1.25	0.03	1.60

Table A.3. Robustness check by controlling other policies

		output		newipr		newproduct		improvement	
		Un-matched	ATT	Un-matched	ATT	Un-matched	ATT	Un-matched	ATT
national	Difference	7982.87	-1174.76	2.55	0.12	3.53	-2.16	3.16	-1.24
	T-stat	1.79	-0.23	4.75	0.08	2.13	-0.47	3.51	-0.55
provincial	Difference	16107.06	5495.05	3.40	1.56	4.07	-4.10	3.94	-0.63
	T-stat	4.22	1.32	7.60	1.20	2.83	-0.76	5.11	-0.24
city	Difference	14094.90	1435.60	3.21	1.49	4.19	3.48	3.79	3.19
	T-stat	3.95	0.66	7.69	2.58	3.14	2.15	5.29	2.66
(A) service policy	Difference	12841.48	3431.60	2.43	2.44	6.33	5.33	1.61	2.15
	T-stat	3.05	1.08	4.76	2.30	4.09	1.53	1.86	1.66
(B) commercialization support	Difference	15454.18	4767.98	3.19	1.14	4.88	0.89	3.75	1.49
	T-stat	4.22	1.71	7.39	1.19	3.56	0.37	5.06	1.20
(C) certification policy	Difference	17847.02	515.32	3.77	3.35	2.98	0.45	3.24	1.43
	T-stat	4.69	0.08	8.54	2.78	2.05	0.17	4.14	1.53
(D) financial and tax incentive	Difference	16341.64	-219.14	1.87	0.44	6.11	2.41	2.68	0.96
	T-stat	4.07	-0.04	3.76	0.40	4.10	0.87	3.25	0.61
(E) talent policy	Difference	8336.81	-25550.38	-0.31	-4.79	9.38	3.12	0.06	-13.54
	T-stat	0.83	-1.15	-0.25	-1.27	2.52	0.23	0.03	-1.35

Table A.4. OLS results for the entire policy dummy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Output)	log(Output)	log(IPR)	log(IPR)	log(new product)	log(new product)	log(improvement)	log(improvement)
Entire policy dummy	1.862***	0.871***	0.837***	0.552***	0.681***	0.496***	0.606***	0.446***
	(0.193)	(0.183)	(0.101)	(0.102)	(0.118)	(0.127)	(0.110)	(0.121)
Log(registered capital)		0.576***		0.150***		0.0982**		0.114***
		(0.0655)		(0.0297)		(0.0413)		(0.0360)
SOE dummy		0.777**		0.224		-0.0774		-0.0898
		(0.339)		(0.223)		(0.310)		(0.252)
FDI and Joint venture dummy		-0.106		-0.126		-0.191		-0.229
		(0.247)		(0.170)		(0.172)		(0.169)
Core district dummy		-0.163		-0.154		-0.260**		-0.286**
		(0.159)		(0.0967)		(0.122)		(0.115)
hightech industry dummy		-0.0903		0.0786		-0.0286		-0.0194
		(0.156)		(0.0970)		(0.118)		(0.109)
Age of firm		0.00891		0.0239		0.0623**		0.0395
		(0.0343)		(0.0195)		(0.0254)		(0.0255)
Square of Age		0.00147		-0.000227		-0.00180*		-0.000981
		(0.00122)		(0.000744)		(0.000943)		(0.00111)
Constant	5.846***	2.761***	0.552***	-0.321**	1.000***	0.394*	0.805***	0.196
	(0.118)	(0.327)	(0.0459)	(0.152)	(0.0648)	(0.228)	(0.0575)	(0.193)
Observations	360	359	394	390	394	390	393	389
R-squared	0.213	0.532	0.162	0.265	0.083	0.144	0.077	0.152

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1 respectively.

Table A.5. OLS results by policy level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Output)	log(Output)	log(IPR)	log(IPR)	log(new product)	log(new product)	log(improvement)	log(improvement)
National	0.368	0.214	0.167	0.148	0.375	0.346	0.282	0.240
	(0.333)	(0.237)	(0.186)	(0.169)	(0.236)	(0.238)	(0.201)	(0.192)
Provincial	0.329	0.325	0.429**	0.404**	0.189	0.131	0.235	0.262
	(0.345)	(0.238)	(0.201)	(0.184)	(0.231)	(0.223)	(0.226)	(0.207)
City	1.473***	0.407*	0.761***	0.510***	0.520***	0.371*	0.564***	0.421**
	(0.291)	(0.221)	(0.173)	(0.160)	(0.198)	(0.193)	(0.194)	(0.176)
Log(registered capital)		0.591***		0.129***		0.0910**		0.0966***
		(0.0676)		(0.0285)		(0.0408)		(0.0348)
SOE dummy		0.818**		0.163		−0.124		−0.155
		(0.336)		(0.200)		(0.329)		(0.254)
FDI and Joint venture dummy		−0.0811		−0.140		−0.192		−0.245
		(0.255)		(0.167)		(0.168)		(0.163)
Core district dummy		−0.106		−0.130		−0.226*		−0.266**
		(0.160)		(0.0901)		(0.117)		(0.109)
hightech industry dummy		−0.114		0.0424		−0.0515		−0.0515
		(0.163)		(0.0912)		(0.114)		(0.104)
Age of firm		0.00603		0.00912		0.0553**		0.0254
		(0.0351)		(0.0187)		(0.0268)		(0.0253)
Square of Age		0.00171		0.000304		−0.00151		−0.000435
		(0.00126)		(0.000714)		(0.000981)		(0.00104)
Constant	6.093***	2.809***	0.584***	−0.145	1.054***	0.493**	0.816***	0.348*
	(0.112)	(0.342)	(0.0433)	(0.144)	(0.0604)	(0.229)	(0.0525)	(0.192)
Observations	360	359	394	390	394	390	393	389
R-squared	0.186	0.520	0.263	0.333	0.110	0.161	0.136	0.195

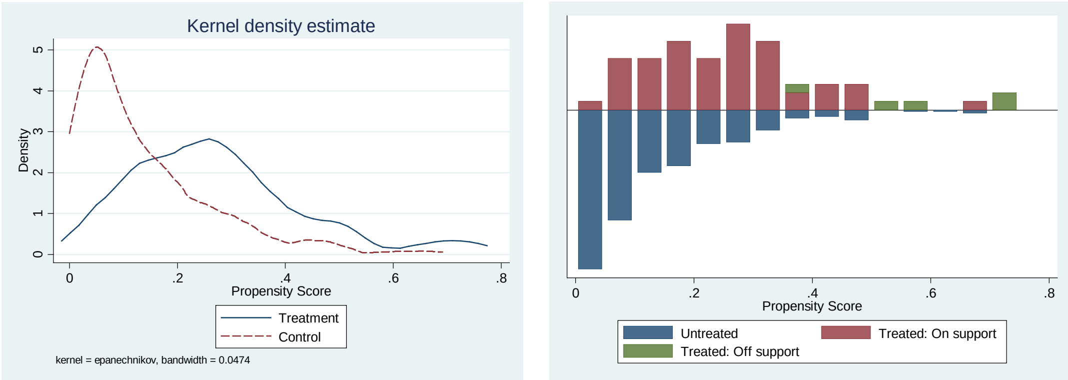
Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1 respectively.

Table A.6. OLS results by policy category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Output)	log(Output)	log(IPR)	log(IPR)	log(new product)	log(new product)	log(improvement)	log(improvement)
(A) service policy	0.620***	0.233	0.360**	0.283*	0.343**	0.334*	0.241	0.204
	(0.237)	(0.204)	(0.144)	(0.145)	(0.173)	(0.178)	(0.156)	(0.164)
(B) commercialization support	1.000***	0.518**	0.642***	0.555***	0.566***	0.483**	0.792***	0.694***
	(0.248)	(0.202)	(0.154)	(0.149)	(0.191)	(0.193)	(0.178)	(0.178)
(C) certification policy	1.095***	0.598***	0.829***	0.683***	0.156	0.0245	0.114	0.0461
	(0.274)	(0.230)	(0.154)	(0.148)	(0.177)	(0.175)	(0.164)	(0.156)
(D) financial and tax incentive	0.687***	0.360*	−0.0519	−0.116	0.253	0.212	0.0646	0.0160
	(0.262)	(0.208)	(0.139)	(0.141)	(0.180)	(0.181)	(0.162)	(0.156)
(E) talent policy	0.286	0.284	−0.493*	−0.440*	0.398	0.450	−0.256	−0.229
	(0.636)	(0.394)	(0.277)	(0.255)	(0.398)	(0.388)	(0.363)	(0.315)
Log(registered capital)		0.546***		0.112***		0.0757*		0.0937***
		(0.0662)		(0.0279)		(0.0401)		(0.0348)
SOE dummy		0.676**		0.127		−0.168		−0.152
		(0.328)		(0.204)		(0.301)		(0.253)
FDI and Joint venture dummy		−0.138		−0.116		−0.209		−0.206
		(0.248)		(0.149)		(0.168)		(0.160)
Core district dummy		−0.135		−0.130		−0.223*		−0.251**
		(0.153)		(0.0886)		(0.119)		(0.110)
hightech industry dummy		−0.159		−0.000185		−0.0706		−0.0776
		(0.156)		(0.0894)		(0.117)		(0.105)
Age of firm		−0.00181		0.00843		0.0659***		0.0345
		(0.0320)		(0.0175)		(0.0246)		(0.0257)
Square of Age		0.00169		0.000209		−0.00203**		−0.000879
		(0.00117)		(0.000658)		(0.000882)		(0.00111)
Constant	5.875***	3.008***	0.525***	−0.0677	0.997***	0.510**	0.796***	0.334*
	(0.112)	(0.340)	(0.0456)	(0.143)	(0.0632)	(0.222)	(0.0568)	(0.189)
Observations	360	359	394	390	394	390	393	389
R-squared	0.290	0.552	0.318	0.374	0.132	0.181	0.147	0.199

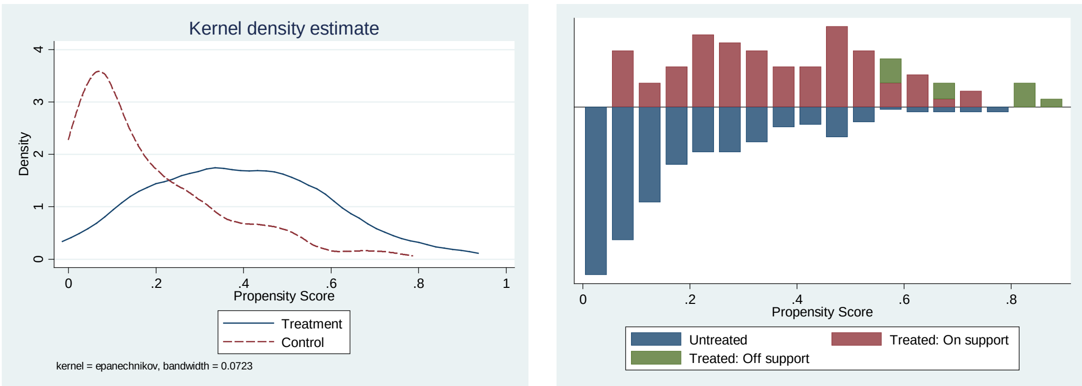
Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1 respectively.

Figures A.1-a and A.1-b. Propensity scores of national policy and their matching results



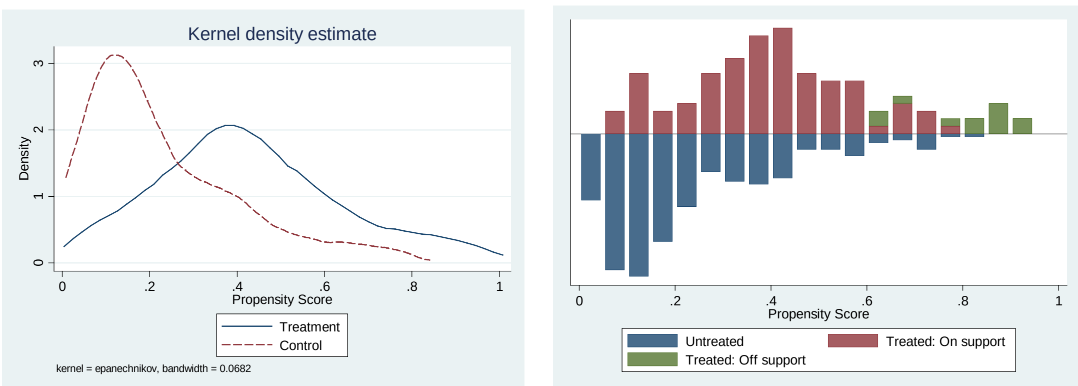
Note: Average matching bias is 8.3% and 5 of 59 treated observations are off support.

Figures A.2-a and A.2-b. Propensity scores of provincial policy and their matching results



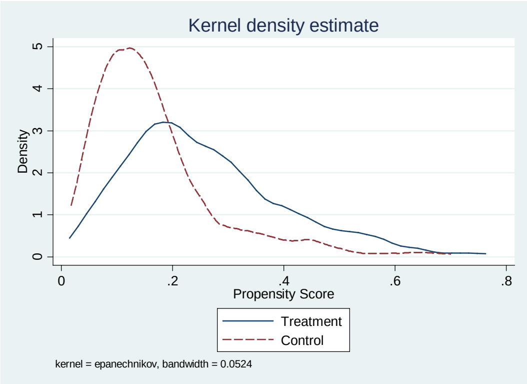
Note: Average matching bias is 9.7% and 9 of 85 treated observations are off support.

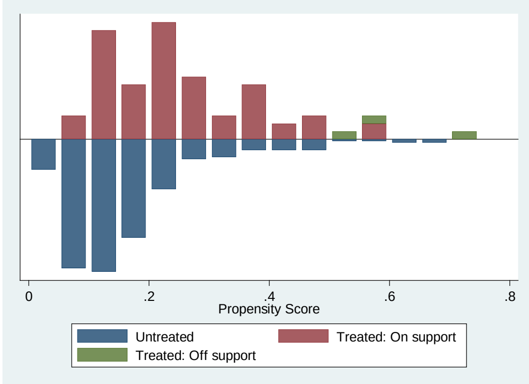
Figures A.3-a and A.-b. Propensity scores of city policy and their matching results



Note: Average matching bias is 12.9% and 12 of 106 treated observations are off support.

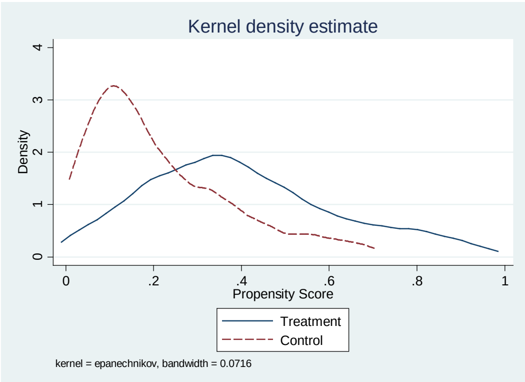
Figures A.4-a and A.4-b. Propensity scores of service policy and their matching results

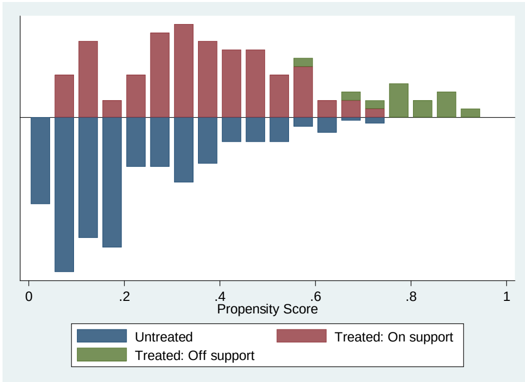




Note: Average matching bias is 13.1% and 3 of 67 treated observations are off support.

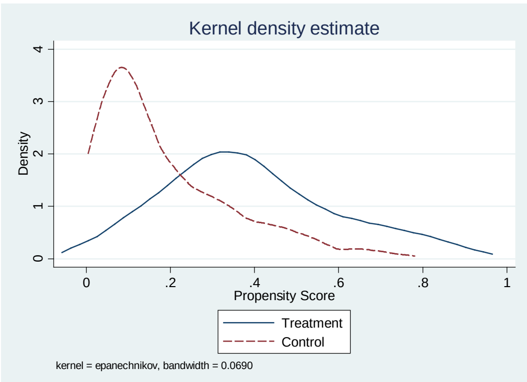
Figures A.5-a and A.5-b. Propensity scores of commercialization policy and their matching results

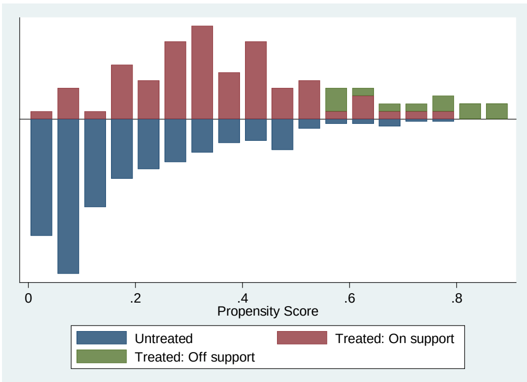




Note: Average matching bias is 10.0% and 13 of 96 treated observations are off support.

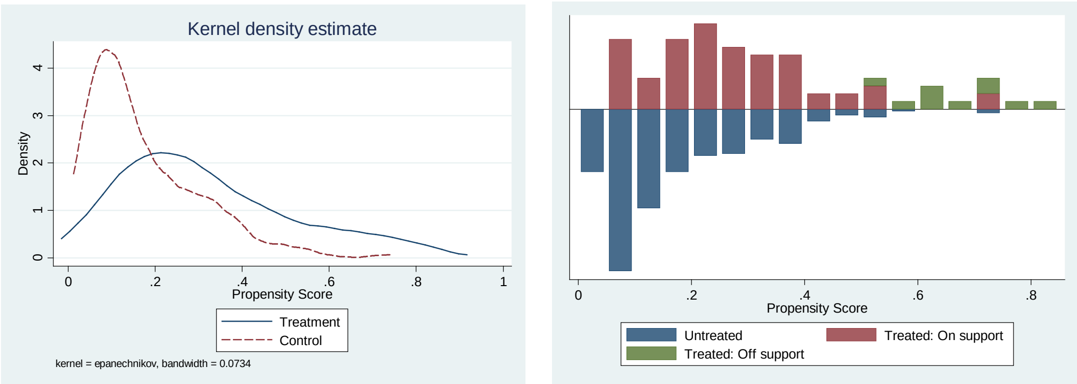
Figures A.6-a and A.6-b. Propensity scores of certification policy and their matching results





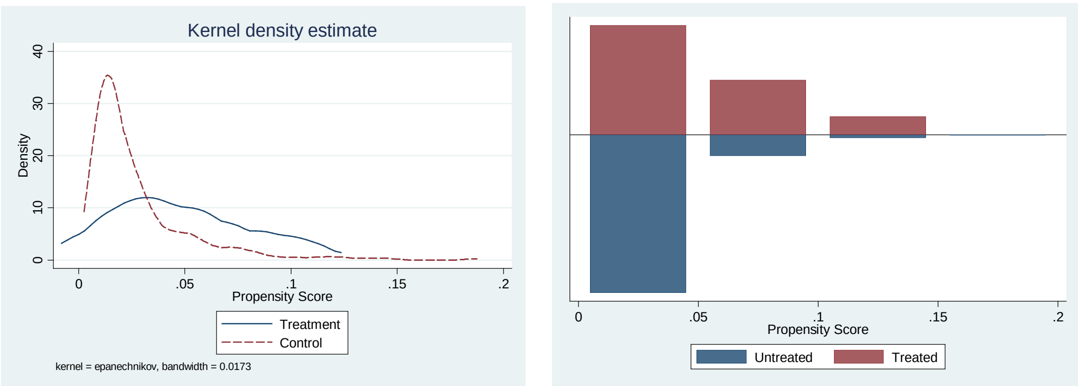
Note: Average matching bias is 9.4% and 12 of 84 treated observations are off support.

Figures A.7-a and A.7-b. Propensity scores of financial and tax incentive policy and their matching results



Note: Average matching bias is 5.8% and 10 of 74 treated observations are off support.

Figures A.8-a and A.8-b. Propensity scores of talent policy and their matching results



Note: Average matching bias is 15.8% and none of 10 treated observations is off support.

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