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Impact of the InnoCom program on corporate innovation performance in China: Evidence from Shanghai

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ABSTRACT

Based on the data from the Shanghai Science and Technology Enterprises survey 2011 to 2015, this paper evaluates how the InnoCom program of stimulating corporate research and development (R&D) implemented in China affects the innovation performance of beneficiary firms from both theoretical and empirical perspectives. We first develop a unified framework considering innovation inputs, absorptive capacity and innovation outputs. Then, we explore the mechanism by which companies with evaluation scores exceeding a certain threshold are more likely to be certified as high and new technology enterprises that qualify for the InnoCom program, and use a fuzzy regression discontinuity design to test whether the policy increases internal R&D inputs, profit, and the number of independent intellectual property rights. After correcting for potential endogeneity problems, the result confirms a positive, significant, and lasting impact of the InnoCom program on high-tech income and the number of intellectual property rights. Meanwhile, there is no significant impact on immediate corporate innovation investment, which suggests a crowding-out effect of government direct subsidies on a company's internal innovation investment. These conclusions are further confirmed by robustness tests. Our findings will help the government understand implementation effect of innovation policies and support them seeking to formulate more effective innovation strategies.

1. Introduction

Continuing innovation, diffusion, and technical improvement are widely recognized as main stimuli to national economic growth and international competitiveness in industrial, newly industrialized, and emerging economies (Archibugi et al., 1991; Ernst and Kim, 2002; Guan and Chen, 2012). As China's industrialization has entered a mature stage, the country's leaders have focused on nurturing technology-intensive industries as a source of future growth (Ding and Li, 2015). Corporate technological innovation has become the leading force for a country to increase its overall competitiveness. The government of China has launched a series of encouragement policies to increase support for corporate research and innovation activities, but whether these policies can achieve their expected goals is debatable. As a guiding policy, how has the InnoCom program affected the innovation performance of enterprises?

Existing economic theories show that imperfect appropriability, spillovers, and uncertainty of a company's innovation output make it difficult for the company to completely internalize the benefits of R&D investment. Therefore, if there is no external support, the equilibrium level of private resources allocated to R&D will be lower than the social optimal level (Spence, 1984). To achieve the optimal allocation of innovative resources and reduce the financing costs and information asymmetries between developers and borrowers, most countries have formulated policies or programs to support corporate R&D activities through tax reductions, fiscal subsidies, and other incentives. These policies are intended to reduce the cost of R&D expenditure for companies and thus stimulate research investment.

There is abundant literature on the effectiveness of the commonly used policy instruments of government R&D subsidies and tax credits on corporate innovation performance on basis of empirical findings (e.g. Bronzini and Piselli, 2016; Cappelen et al., 2008; Girma et al., 2007; Lokshin and Mohnen, 2012). However, little empirical evidence has shown whether or not the whole program truly benefits companies and to what extent. In contrast with the widely investigated policy instruments in the existing literature, the InnoCom program we studied is rather unique and has been implemented in China for more than ten years. The InnoCom program in China is a policy tool that targets qualified firms, accrediting them as high and new technology enterprises (HNTEs) and giving them preferential tax, financial support, and other local favorable policies. The supposed mechanism behind the InnoCom program is that public incentives are expected to stimulate

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enterprises' internal research and development, and these additional induced research activities will be conducive to the emergence of new products and new technologies (Czarnitzki and Hussinger, 2004). However, firms may apply for HNTEs to arbitrage away the benefits associated with the program without improving the corporate innovation performance. Furthermore, companies often send fake "innovation" signals to get government R&D subsidies such as relabeling other expenses as R&D expenditures (Chen et al., 2018), making the technological and economic benefits of the InnoCom program questionable.

In this paper, we study the influence of the InnoCom program implemented in Shanghai on enterprises' innovation performance from theoretical and empirical perspectives. We choose Shanghai because it is one of the most active and innovative economic zones in China and plays an increasing significant role in national economic growth.[1] Our theory formulates five testable hypotheses suggesting that the influence of policy on innovation outputs has two main channels: the increase of a company's total innovation inputs and the improvement of absorptive capacity. The empirical results confirm these two channels and show that the InnoCom program has no significant influence on internal R&D inputs but improves innovation performance as measured by new and high technology products' (services') income and the number of independent intellectual properties.

This paper contributes to the existing literature in several ways. First, we develop a unified framework to investigate the relationships among government policy instruments, firms' innovation inputs, absorptive capacity and innovation outputs. Second, and most importantly, we adopt a fuzzy regression discontinuity design with a quasi-random identification strategy to study the causal effect of the InnoCom program on enterprise innovation performance, handling the issue of endogeneity problem in the regression. Furthermore, we evaluate the InnoCom program from both the input side and output side of the R&D process since both sides will be influenced by the policy. Theoretical analyses and estimation results in this paper are not only of great interest to the Chinese government, but also provide useful reference for governments of other emerging economies promoting innovation development.

The remainder of this paper is organized as follows. Section 2 describes the major policies and mechanisms of the InnoCom program. Section 3 reviews the relevant literature on the relationships among policy instruments, innovation input, absorptive capacity and innovation performance, and gives a theoretical framework with five hypotheses. Section 4 introduces the data and relative variables. Section 5 provides the empirical strategy. Section 6 presents the estimation results and robustness tests. Section 7 gives conclusions and recommendations.

2. Background of the InnoCom program

Since the 1990s, the Chinese government has issued a series of accreditation policies for enterprises in the national high-tech development zone to encourage technological innovation. In 2008, the *Administrative Measures for the Determination of High and New Technology Enterprises* (2008) (hereinafter referred to as *Administrative Measures*) was promulgated, which expanded the coverage of HNTE accreditation to enterprises outside the high-tech development zone and unified the certification standards and operational procedures nationwide. The *Administrative Measures* was revised in January 2016 to further expand the scope of certification, increase support for innovative enterprises, especially small and medium-sized enterprises, and encourage more companies to increase R&D investment.

The InnoCom program implemented by China, which targets high-tech enterprises, is an attempt from the Chinese government to address the challenge of improving enterprises' core innovation capabilities through the following channels. Depending on the forms of subsidy, preferential terms can be classified into three categories: R&D funding, R&D cost deductions, and tax credits. The first one varies with the location of the company, and the last two are national unified polices. R&D funding is provided to motivate companies to get involved in the program, and to enhance the technological prowess of the economy (Czarnitzki and Fier, 2002). For the proportional R&D cost deductions, an enterprise can additionally calculate and deduct the R&D expenditures that have been registered and occurred in the calculation of the taxable income amount. Unlike direct subsidies, companies need to invest a certain amount of money before they get the corresponding proportion of deduction. These features make policies more likely to generate positive incentive effects; the more capital that companies invest, the more deduction they enjoy. Among the three policies implemented by policymakers to strengthen innovation activities, tax credits are regarded as the most important instrument for encouraging innovation because it allows for flexible responses to new challenges. According to the *Law on Corporate Income Tax* (2008), HNTEs can enjoy a preferential tax rate of 15%, which is 10% points lower than the 25% standard income tax rate. The incentive mechanism of tax credits is similar to proportional R&D cost deductions, as both require companies to invest in advance to get preferential treatment.

In addition, as a national-level certification, the accreditation of HNTEs will effectively improve the core competitiveness of enterprises, provide strong qualifications for enterprises in the market, and greatly promote the brand image of enterprises, which can help tremendously in terms of advertising and bidding.

In Table 1, we represent the most important determinants of an HNTE according to the *Guidelines on the Administration of Determination of High and New Tech Enterprises* (2008) (herein after referred to as *Guidelines*).

To be an HNTE, the firm is required to apply and submit to a special audit and satisfy all four conditions in Table 1. By the end of 2017, the number of certified high-tech enterprises in Shanghai had exceeded 7000. However, there may be problems with certification. A certain amount of unqualified companies obtain certification in a variety of ways to get the policy preferences, so the implementation of this policy has been questioned by many parties. People's Daily Online, China News, Southern Metropolis Daily, and Economic Information Daily have published articles on the phenomenon of "pseudo-high-tech"[2] many times, and there are a plethora of high-tech enterprise certification agencies. Nevertheless, research on the impact of the InnoCom program on the innovation ability of Chinese enterprises is still largely absent. Whether this policy has promoted the industrial development of high-tech enterprises in China and promoted the core innovation of Chinese enterprises is still in question. This paper contributes to this stream of research by using microdata to examine the impact of high-tech enterprise certification on the innovation performance of companies.

The mechanism of the InnoCom program allows us to compare the innovation performance of HNTEs and non-HNTEs close to the cut-off score, using a fuzzy regression discontinuity (FRD) design (Hahn et al., 2001; Lee and Lemieux, 2010). Firms that score above a certain level in an evaluation by the confirmation authority would be certified, so we can estimate the policy effect using the quasi-randomness of the assignment of HNTE certifications around the threshold, which makes HNTEs and non-HNTEs comparable.

One particular concern is that accreditation is not the only way to

[1] From *Report of China Regional Science and Technology Innovation Evaluation 2016–2017*.

[2] According to the article "Pseudo-high-tech companies gathered in the Growth Enterprises Market, 27 companies enjoy tax benefits of 261 million yuan", from January 1 to March 21, 27 companies of 148 HNTEs in GEM did not meet the conditions for high-tech enterprise certification. (*Economic Information Daily* March 30, 2012)

Table 1
Requirements for HTNE certification.

A weighted score of four indicators	Number of independent intellectual property rights[1] (30 points)	> 70
	Capacity of transformation of scientific and technological achievements (30 points)	
	Level of organization and management of research and development (20 points)	
	Growth in sales and total assets (10 points + 10 points)	
R&D Intensity	If the sales revenue < 50 million yuan	≥6%
	If the sales revenue is 50–200 million yuan	≥4%
	If the sales revenue > 200 million yuan	≥3%
Income	Revenue from high-tech products (services) of its total revenue	≥60%
Human capital input	Percentage of staff with advanced degrees	≥30%
	Percentage of R&D staff	≥10%

[1] The number of independent intellectual property rights is the sum of the number of patents, software copyrights, layout designs of integrated circuits and and new varieties of plants a firm owns (excluding trademarks).

access innovation subsidies so that the treatment variable (being certified as an HNTE) cannot capture the true effects. In fact, there are indeed other innovation policy schemes where being accredited is not a compulsory term.[3] However, the InnoCom program is more important when compared with simple regional subsidies, regardless of whether we analyze it from a scale or social influence perspective. An HNTE will also be given priority when it applies innovation subsidies. Being an HNTE will effectively improve the competitiveness of enterprises and enhance their reputation since the certificate is jointly awarded by *China's Ministry of Science and Technology, Treasury* and *State Administration of Taxation*. In addition, as we discussed before, the primary policy instrument of the InnoCom program is tax credits (Chen et al., 2018; Liu et al., 2018). Tax credits is a national unified policy tool which is stated in the *Certification Measures*, *Law on Corporate Income Tax*, and its *Implementation Regulations*. Preferential taxation policies such as 15% favorable income tax rates and R&D expenses deductions will cut down firms' cash outflow to a certain degree, improving the financing capacity for R&D activities (Duchin et al., 2010). Moreover, the amount of tax relief is a lot greater than the subsidy that a firm can obtain. Hence, the treatment variable provides at least a certain degree of the true effects of the whole program.[4]

3. Theory and literature review

3.1. The impact of the InnoCom program on innovation inputs

The relationship between innovation policies and a firm's innovation inputs has attracted widespread attention among economists and policymakers regarding whether and/or how effective policies are for encouraging R&D. In relation to R&D subsidies, both positive and negative incentive effects exist in the literature. Government expenditure on R&D, as a policy instrument capable of stirring regional innovation policy, can incentivize enterprises to divert funds into research and positively influence the regional innovation inputs (Correa et al., 2013; Gkypali et al., 2016; Guellec and van Pottelsberghe, 2003). However, scholars have also found evidence of crowding-out effects through theoretical models and empirical studies (David et al., 2000; Wallsten, 2000). One form of crowding-out is that enterprises could have invested in the projects with higher success probabilities and high private rates of return by using either internal or external funds, suggesting that the research grants are in fact unnecessary and may be crowding out private investments (Lach, 2002). The subsidy is "crowding out" an investment that would otherwise be firm expenditure because government subsidies reduce R&D risks and capital costs (Lee and Cin, 2010). Companies can transfer some of their own funds from projects that are profitable but risky to productive areas after receiving subsidies so that they can use fewer funds to obtain project benefits and avoid risks, which in turn produces the crowding-out effect.

In contrast to direct subsidies, tax incentives are not subject to public selection, and all eligible firms can claim support. Therefore, tax credits are considered to be a more neutral policy instrument. Firm-level evidence on the effectiveness of tax incentives tends to report input additionality (Hall and Van Reenen, 2000; Lokshin and Mohnen, 2012; Mohnen et al., 2017). However, existing findings show considerable variations depending on the data, estimation methods, and model specifications (Becker, 2015). Furthermore, tax credits arguably do not directly address market failure associated with innovation activities, and they may make firms focus on R&D projects with high private returns rather than projects with high social returns (Czarnitzki et al., 2011; David et al., 2000; Hall and Van Reenen, 2000).

We develop and discuss a simple and stylized model of innovation investment whereby firms respond to three preferential policies (see Appendix). This model yields the following theoretical results: First, an increase in the R&D cost deductions and tax credits increases the number of research inputs at the stationary equilibrium, which will also bring about a higher probability of innovation and enterprise value. Second, direct government funding leads to lower enterprise internal research input, whereas the number of total investments stays the same, that is, firms will use government funds to replace internal R&D investment. Hence, we develop the following hypotheses:

H1a. The InnoCom program has a negative impact on enterprise internal R&D expenditure.

H1b. The total effect of the InnoCom program on firms' total innovation inputs is positive.

3.2. The impact of the InnoCom program on absorptive capacity

It can be argued that innovation policies stimulate firms to augment their internal competencies and capabilities, i.e. its absorptive capacity. As we discussed before, the InnoCom project is an incentive policy that encourages enterprises to innovate and improve their core innovation capabilities. Moreover, the accreditation of HNTEs can greatly promote the brand image of enterprises, which positively affects the diversity of R&D collaborators and then enhances firms' technological competences and, even more, capabilities (Gassmann and Enkel, 2004; Iammarino et al., 2012; Kokshagina et al., 2017). In addition, R&D funding can lead to commercializable innovations and improve firms' ability to understand and absorb knowledge from outside the industry and from rival firms (Watkins and Paff, 2009). In this context, an indirect effect related to internal innovation efforts exists, originating from policy incentives, mediated by the internal innovation process and then resulting in the improvement of internal absorptive capacity. Based on the above analysis, we formulate the following hypothesis:

H2. The total effect of the policy instruments on enterprise absorptive capacity is positive.

[3] Taking Changning District Shanghai as an example, the district government will grant 100,000 yuan to a district-level innovation project. However, > 80% of the HNTEs enjoy over 100,000 yuan in tax benefits in our data. We are grateful to a referee for pointing out this issue to us.

[4] In the section of Robustness, we get the similar results after controlling firms' annual R&D subsidies from the government.

3.3. Innovation performance: the influence of innovation inputs and absorptive capacity

Although the transformation process of innovation inputs to innovation outputs remains a black box (Rosenberg, 1982), there are some conceptual and empirical studies in which innovation inputs are directly related to innovation performance. Core technological know-how in innovation lies at the center of a circle of complementary assets and technologies needed to commercialize innovation (Teece, 2006), which are expected to positively and directly influence firms' innovation performance (Gkypali et al., 2017). The empirical analyses also show a positive relationship between regional innovation inputs and regional innovation outputs (Cai and Xu, 2008; Gkypali et al., 2016). Although innovation inputs arguably have indirect and negative effects on innovation performance, mediated by the diversity of R&D collaborators and the rise in cost (Gkypali et al., 2017), it is reasonable to assume that direct effects may dominate. In line with prior empirical findings, we propose the following hypothesis:

H3. Firms' innovation inputs have a positive influence on their innovation performance.

Besides the impact of innovation inputs, the role of absorptive capacity has been highlighted to explain various organizational phenomena and competitive advantages (Fosfuri and Tribó, 2008; Zahra and George, 2002). More specifically, successful transformation of resources into capabilities and conversion of new developments to appropriate returns are conducive to improving productive performance (Antonelli and Colombelli, 2011; Gkypali and Tsekouras, 2015; Klevorick et al., 1995). Schilling (1998) argues that through absorptive capacity, enterprises improve their ability to assimilate information, and eventually to enhance their technical level. Moreover, Chen et al. (2009) utilize structural equation modeling (SEM) and conclude that relationship learning and absorptive capacity have a positive influence on innovation performance. Gkypali et al. (2018) develop a unified framework and provide empirical evidence that enterprises' absorptive capacity directly and positively influences innovation performance. Therefore, the absorptive capacity of firms would affect their innovation outputs, and we develop the following hypothesis:

H4. Firms' absorptive capacity has a positive influence on their innovation performance.

3.4. The theoretical framework

Fig. 1 below presents a graphical representation of the theoretical framework. We will empirically examine the complex relationships between the InnoCom program and three main variables: innovation inputs, absorptive capacity, and innovation outputs.

4. Data

Our analysis is based on the science and technology enterprises annual statistical data collected by the Shanghai Science and Technology Committee (STCSM) during the period 2011–2015, which provides information about medium-and small-size science and technology enterprises[5] in Shanghai. All firms contained in the sample were required to complete an identical and specially designed questionnaire asking about firms' basic information and innovation activities. In particular, the first part involved company code, ownership, assets, liability, income, number of employees as well as other questions related to production and operation. Apart from the key information of firms, a series of questions regarding R&D outputs, R&D investments, and whether the company is an HNTE were asked. Although the statistical information includes whether the enterprise had been certified as an HNTE or not, there was no specific date as to when the company was identified and the number of new and high technology transformation achievements was not reported, which is also an important assessment indicator when calculating the score. To make up for this deficiency, we use the relevant information published online by the Shanghai Science and Technology Committee,[6] which provides an HNTE list every year and information on new and high technology achievement transformation.

In order to study the performance of enterprises identified as HNTEs in 2012, we pool together and match the yearly data from 2011 to 2015 by using the company code. More specifically, we measure T_i based on the accreditation status of the HNTE in the following year. In other words, T_i is a dummy variable that takes the value of 1 if enterprise i was identified as an HNTE during 2012, and 0 otherwise. For companies identified as HNTEs in 2012, the accreditation is based on their performance prior to 2012, which indicates that the comprehensive scores are calculated by using enterprise characteristics from 2011 according to the four evaluation criteria in the *Guidelines*, as listed in the first line of Table 1. Enterprises scoring > 70 points meet the HNTE certification standards.[7] As introduced in the previous section, all four conditions (a weighted score of four indicators, R&D intensity, income, and human capital input) must be met simultaneously, otherwise, the score will be zero. The empirical strategy of this paper is based on the comprehensive score of each company, we exclude those companies that have not received a score (score equal to zero) because they did not satisfy at least one of the requirements. Given that the strategy is based on the discontinuity test around the cut-off score, and omitted companies would have gotten the total points far away from the threshold, hence the exclusion does not affect our empirical results (Bronzini and Piselli, 2016). After data cleaning, the remaining number of companies is 1725, of which 764 are HNTEs.

We consider three outcome variables stemming from the theoretical model to test the above five hypotheses, namely, innovation inputs, absorptive capacity, and innovation outputs. The innovation inputs are approximated by four indicators, internal innovation expenditure (*IRD*), government R&D funding (*GRD*), total innovation inputs (*RDtotal*) and R&D staff (*RDstaff*). Consistent with the *Guidelines*, we define internal innovation expenditure = Enterprise R&D expenditure + 0.8* Outsourcing R&D expenditure and define the total innovation input as the summation of internal innovation expenditure and government R&D funding. *lnIRD* and *lnRDtotal* are defined as the logarithm of the company's internal annual innovation expenditure and total innovation input. In addition to capital input, we use the ratio of staff in high-tech sectors to the total number of employees as a proxy for human capital input. Then, absorptive capacity is measured by the logarithm of the company's R&D capital stock (*lnRDstock*) and the ratio of high-degree employees[8] to the total number of employees (*HDstaff*). Finally, we measure corporate innovation output using economic performance of innovation (*lnHTInc*) and number of Independent Intellectual Property rights (*IIP*), where *lnHTInc* is defined as the logarithm of the company's annual new and high-tech product (service) revenue, and *IIP* is the sum of the number of patents, software copyright registrations, and layout design registrations of integrated circuits a firm owns. Multivariate innovative indicators are used to analyze the impact of the InnoCom program on Chinese firms' innovation performance.

Table 2 reports the descriptive statistics of samples with scores

[5] Both HNTEs and non-HNTEs in Shanghai.

[6] http://www.stcsm.gov.cn/

[7] However, we don't have the data about level of organization and management of research and development. Judging from the audit mechanism, we believe that scores are closely related to the application materials, so we set the same scores (20 points) to all enterprises.

[8] Employees with bachelors, masters or doctorate degrees.

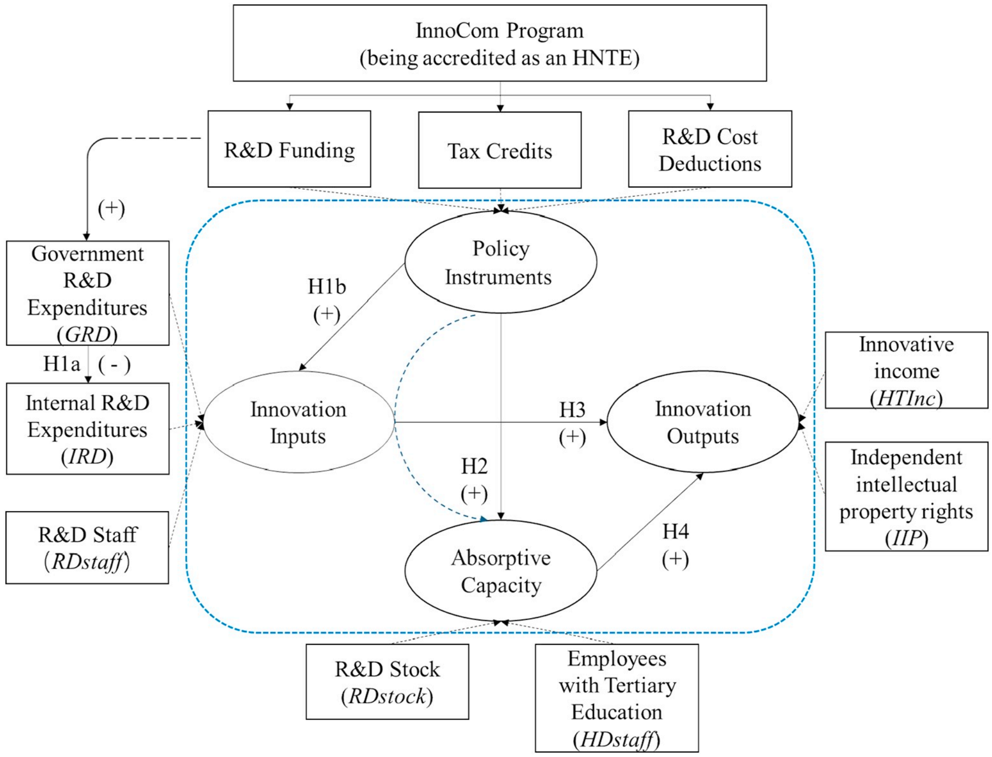

Fig. 1. Theoretical framework.

Table 2
Enterprise descriptive statistics.

Variable	Indicator	Symbol	All (score > 0)	Cut-off-5	Cut-off + 5	*t*-test (H_0: diff = 0)
Enterprise economic performance	Total income	*Inc*	68,522.14	106,125.10	60,823.28	0.56
	New and high technology products (services) income	*HTInc*	9310.91	2976.44	9442.55	0.10
Independent intellectual property rights	Patents	*Pat*	2.28	2.28	2.8	0.70
	Invention patents	*IPat*	0.65	0.64	0.875	0.59
	Software copyright registrations	*SC*	1.50	2.61	2.875	0.75
	Layout designs of integrated circuits	*LD*	0.04	0.14	0.075	0.63
Material capital input	Government R&D funding	*GRD*	902.63	2258.74	9989.15	0.28
	Enterprise R&D expenditure	*ERD*	5988.33	8603.27	9571.725	0.88
	Outsourcing R&D expenditure	*ORD*	175.58	192.34	464.025	0.36
Human capital input	R&D staff	*RDstaff*	32.77	38.70	63.65	0.25
Absorptive Capacity	Doctors	*Doc*	1.02	1.20	2.38	0.41
	Masters	*Mas*	7.80	10.19	17.725	0.55
	Undergraduates	*Und*	28.83	33.45	39.875	0.67
	R&D stock	*RDstock*	503.42	315.95	496.30	0.11
Others	Total employees	*Emp*	91.25	104.57	126.2	0.58
	Total Assets	*Asset*	95,650.30	126,916.40	171,684.60	0.59
	Total Liabilities	*Liab*	52,940.58	67,287.40	59,943.65	0.85
Indicator scores	The score of independent intellectual property rights	*Siip*	8.18	15.04	14.12	0.63
	The score of capacity of transformation	*Sct*	29.18	21.33	29.09	0.00
	The score of growth in sales	*Ss*	8.15	9.32	9.29	0.23
	The score of growth in total assets	*Sta*	8.40	9.48	9.75	0.20
N			1725	89	40	

This table reports firms' characteristics in 2012. The unit of enterprise economic performance, material capital input, R&D stock and others is thousands of RMB yuan and "Independent intellectual property rights" is measured in "number of independent intellectual property rights that the firm has achieved over the past year". N is the number of observations with at least one non-missing value for the variable listed.

above zero and five points around the cut-off. We report input and output variables that are used to construct measures of enterprise performance, including enterprise economic performance, independent intellectual property rights, material capital input, human capital input, and some other variables. The fourth column shows the characteristics of samples with scores higher than zero. On average, the income of new and high technology products (services) exceeds 90 million yuan, the number of independent intellectual property rights is 4.47, the number of employees with tertiary education (doctorates, masters, and bachelors) is 37.65, and the number of researchers is 32.77.

The regression discontinuity estimation assumes that the treatment is random near the cut-off, so that enterprise characteristics should not differ significantly just below and above the threshold. The penultimate and antepenultimate columns report the summary statistics for 5 points around the cut-off point. We apply the *t* statistic to test the hypothesis that their means are equal, above and below the cut-off, and provide *p*-

values in the last column. There are no significant differences in the number of firms' patents, invention patents, software copyright registrations, layout designs of integrated circuits, enterprise internal R&D expenditure, total employees, total assets and total liabilities between the left and right side of the cut-off since the p-values of the *t*-test are all above 0.5, meaning we cannot reject the null hypothesis.[9] By contrast, the difference is more pronounced in terms of the company's new and high technology products (services) income. It rises more than threefold as the score increases, which implies that the certification may have a certain impact on business performance. Overall, these findings support our empirical strategy.

5. Empirical strategy

Most studies assess whether R&D incentives have a promotional effect using standard policy evaluation methods, such as OLS, fixed effects panel regression, difference-in-differences (DID) (Chen and Gupta, 2010; Dumont, 2017; Guan and Yam, 2015; Guceri and Liu, 2015). However, innovation incentives may have a self-selection bias and reverse causality because the revealed better performance of firms receiving the promotion may be because they are better firms and better firms are more likely to get the promotion. In our case, the systematic differences between HNTEs and non-HNTEs are probably the reasons that the former enjoy favorable policies, so OLS and DID estimation will bring biased results and a fixed-effect estimation cannot fully overcome this endogeneity.

In addition, Gkypali and Tsekouras (2015) adopt a full-information maximum-likelihood (FIML) to simultaneously estimate binary and continuous parts of the model in order to handle both the issues of endogeneity and sample selection, which gives consistent standard errors.[10] However, this approach relies on two strong assumptions which are homogeneous error terms in the binary equation and joint normality of the error terms in the binary and continuous equations (Maddala (1983) p. 223–224). Thus, when the assumptions are violated, it can cause unavoidable inaccuracy. Gkypali et al. (2018) employ structural equation modeling (SEM) to depict the complex relationships between key variables. SEM is effective in testing the hypothesized causal inferences among structural parameters, while it requires that the direction of causality between constructs and their measures should be specified correctly (Jarvis et al., 2003). Potential misspecification of an equation can affect the estimation of the whole structural model. However, the regression discontinuity is designed for evaluating causal effects of interventions in a single equation, avoiding potential misspecification of other equations.

In this paper, in order to control for the endogeneity problem and selection bias in the linear regression, we adopt a fuzzy regression discontinuity design with a quasi-random identification strategy to study the causal effect of the InnoCom program on enterprise innovation performance. The primarily idea behind the regression discontinuity design is that individuals with scores just below the threshold (who did not receive the treatment) are similar and comparable to those just above the threshold (who did receive the treatment), so the difference in output between the individuals on both sides should be caused by the treatment and not affected by the selectivity bias (Lee and Lemieux, 2010). Lee (2008) believes that in the absence of random experiments, regression discontinuity can avoid the endogeneity problem of parameter estimation, so it can reflect the causal relationship between variables.

One key assumption of the regression discontinuity method is that individuals around the cut-off have similar characteristics, which can be tested by statistical analysis. And another general assumption is that the individuals should not be able to precisely control the running variable. In our case such assumptions hold, because the score is obtained by evaluating the companies based on the scoring criteria since the real scores are not observed in our data and it is highly unlikely that firms can perfectly control the score for every category. In Section 6 we conduct some robustness checks to test the validity of the regression discontinuity design. Thus, the discontinuity of the target variable at the threshold can be attributed to the result of a policy.

RD can be divided into sharp regression discontinuity design (SRD) and fuzzy regression discontinuity design (FRD). According to the current mechanism of the HNTE certification, companies should first submit application materials and then the applications are reviewed by expert groups and a verification agency. Therefore, not all companies satisfying the conditions will become HNTEs; the company needs to have the intent first. Meanwhile, in order to obtain the fiscal and taxation benefits, unqualified companies will try to obtain certification in multiple illegal ways, including relabeling innovation costs. Hence, the mechanism of InnoCom program only makes the possibility of being certified have a jump at the cut-off specified in the policy. This feature is consistent with fuzzy regression discontinuity design. The discontinuity can be seen in Fig. 2, which captures key elements of the relation between the running variable (corporate score minus 70 points) and HNTE certification rates. Each point on the chart indicates the probability that companies in each score can be certified as a high-tech enterprise. We can see a clear breakpoint in the certification rate of high-tech companies around 70 points and an increasing probability of certification as we move right from the cut-off (Fig. 2). Therefore, we can use the discontinuity of the rating system to identify the causality between high-tech enterprise certification and corporate innovation performance.

The fuzzy regression discontinuity design allows for a small jump from 0 to 1 in the probability of assignment to the treatment at the cut-off and is usually assumed to be:

$$\lim_{\varepsilon \downarrow 0} \Pr(D = 1 \mid X = c + \varepsilon) \neq \lim_{\varepsilon \uparrow 0} \Pr(D = 1 \mid X = c + \varepsilon), \tag{1}$$

where the dummy variable $D_i(x)$ denotes the treatment of an individual i within a small neighborhood near the cut-off c, so that we have $D = 1$ if $X \geq c$, and $D = 0$ if $X < c$.

In the fuzzy regression discontinuity model, scholars believe that the average causal effect of the experiment should be the ratio of the two differences: the difference of the dependent variable Y on the regression of the covariates X divided by the difference of the treatment variable D at the threshold. This is:

$$\tau_{FRD} = \frac{\lim_{\varepsilon \downarrow 0} \mathbb{E}(Y \mid X = c + \varepsilon) - \lim_{\varepsilon \uparrow 0} \mathbb{E}(Y \mid X = c + \varepsilon)}{\lim_{\varepsilon \downarrow 0} \mathbb{E}(D \mid X = c + \varepsilon) - \lim_{\varepsilon \uparrow 0} \mathbb{E}(D \mid X = c + \varepsilon)}. \tag{2}$$

Hahn et al. (2001) point out that when the treatment effect changes in units, instrumental variables can be used to explain the fuzzy regression discontinuity design, which is consistent with the view of Imbens and Angrist (1994). The fuzzy regression discontinuity leads naturally to a simple two-stage least square (2SLS) estimation strategy (Imbens and Lemieux, 2008; Lee and Lemieux, 2010), so we can use the exogenous assignment mechanism to identify the impact of certification on a firm's innovation performance. Since the treatment depends on whether the running variable exceeds the cut-off point, we can use whether the company scores over 70 points as an instrumental variable

[9] We also test the continuity of characteristics of the company or control variables using the following parametric polynomial discontinuity regression model: $Z_i = \gamma_0 + \gamma_1 D_i + \gamma_2 S + \gamma_3 S^2 + \mu_i$, where Z_i is a characteristic variable of companies, such as the size of the company, asset-liability ratio, the number of employees, and the liabilities of the company. We found no discontinuity for any individual characteristics examined and no significant results for these variables that should not be affected, indicating that the application of a discontinuity regression design method is appropriate. The results, which are not shown, are

available on request.

[10] We thank two anonymous referees for bringing this endogenous treatment method to our attention.

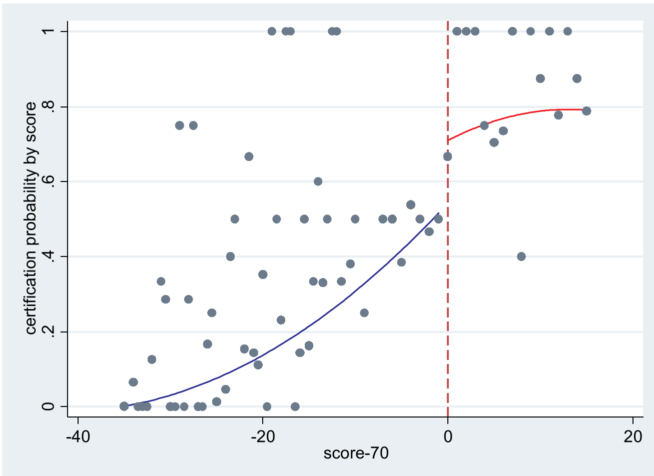

Fig. 2. Running variables and HNTE certification rates.
Notes: The x-axis variable is (actual score-70) and "0" is the cut-off. The y-axis variable is the probability of an enterprise being certified at each specified score.

and limit the sample to a small neighborhood around the threshold. We estimate the effect of the policy using the following parametric polynomial discontinuity regression model:

$$T_i = \alpha_0 + \alpha_1 D_i(score_i - c > 0, D_i = 1) + \alpha_2 S_i + \alpha_3 S_i^2 + \nu_i, \tag{3}$$

where D_i is the excluded instrument that provides identifying power with a first-stage effect given by α_1, and T_i is a dummy variable for certification. T_i is equal to 1 if enterprise i is identified as an HNTE and to 0 otherwise. Specifically, we exploit the fact that an HNTE certification is determined by $D_i = 1(S_i \geq 0)$ where S_i is the difference between the enterprise score and the cut-off point. The second stage regression equation in this case is

$$Y_i = \beta_0 + \beta_1 T_{it} + \beta_2 S_i + \beta_3 S_i^2 + \varepsilon_i, \tag{4}$$

where Y_i is the outcome variable as introduced in Data section and ε_i is the error term. In addition, as per the guidance in Lee and Lemieux (2010), it is necessary to investigate how regression discontinuity estimates are robust to the inclusion of higher order polynomial terms. If we mistake a nonlinear equation for a linear equation and use a regression discontinuity model to estimate, we can also estimate a jump, but the error is quite severe. To reduce the likelihood of such mistakes, we add polynomial terms of S_i to construct the nonlinear relationship, and report the best specification based on the order of polynomial that provides the minimum Akaike information criterion (AIC).

Since high-quality companies are more likely to get higher scores and to be certified, selection bias will happen if we apply OLS to estimate Eq. (4) using the original value of T_i. The reason why the experimental variable D_i can avoid the bias is that the variable D_i is not disturbed by the company's quality and is highly correlated with T_i. In fact, whether or not an HNTE scores 70 according to the scoring mechanism is not a major concern. Our goal is to estimate companies that are truly certified as HNTEs and whether their innovation performance is affected. In order to obtain unbiased estimation of policy effect, we can use D_i as an instrumental variable for T_i, because D_i can predict T_i while being unaffected by the selection bias. Therefore, if the regression discontinuity setting is valid, the above 2SLS regression estimates will be consistent, which can avoid endogeneity problems caused by missing variables. In addition, we verify the validity of the regression discontinuity setting by robustness checks.

Table 3
The first-stage estimates for fuzzy regression discontinuity.

	Dependent variable: whether the firm is certified as an HNTE			
	(1)	(2)	(3)	(4)
D	0.688***	0.437***	0.196***	0.195***
	(0.006)	(0.007)	(0.019)	(0.019)
(score-70)		0.003***	0.012***	0.009***
		(5.97e-05)	(0.001)	(0.001)
$(\text{score-70})^2$			0.0001***	0.0004***
			(7.75e-06)	(2.28e-05)
$(\text{score-70})^3$				4.30e-06***
				(3.36e-07)
Cons.	0.016***	0.217***	0.292***	0.233***
	(0.001)	(0.004)	(0.007)	(0.008)
Obs	1725	1725	1725	1725
R^2	0.387	0.463	0.468	0.473

Standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

6. Results

6.1. Baseline results

This paper analyzes the relationship between HNTE certification and corporate innovation performance. According to the validity of regression discontinuity, we should control the non-linear continuity effect of the score above and below the threshold. In the regression discontinuity estimation below, this non-linear relationship is constructed by multiple order terms of S. Table 3 lists the estimation results of how the rating system affects HNTE certification. The explanatory variables are whether or not they are recognized as new and high-tech enterprises. The coefficients in column (1)–(4) turn out to be positive and statistically significant at the 1% level in all the specifications, suggesting that scores exceeding the threshold indeed increase the probability of the company being certified.

The results in Table 3 are from the first stage regression. In the following, we will focus on the main regression equation (the impact of the certification on the explanatory variables, i.e., the second stage). Lee (2008) uses a voting example and shows that if the regression discontinuity design is valid, adding any combination of covariates essentially has no influence on the regression discontinuity estimates. Adding a set of covariates does not have a large influence on the standard errors either, at least up to the third decimal. Table 4 shows the 2SLS estimation results of the policy impact on innovation inputs, absorptive capacity and innovation outputs in the current year, where no other control variables were added except for whether they were identified as HNTEs, the instrumental variable (score dummy variable), and polynomial terms of S. The results show that four out of the five hypotheses formulated in Section 2 are confirmed.

With respect to H1a and H1b, the empirical results indicate that the program has no significant impact on enterprise internal R&D expenditure while it has a positive effect on firms' total innovation inputs. More specifically, from the result in columns (2), we can see there is no significant effect of certification on enterprise internal innovation input, although the coefficient is positive. Czarnitzki and Hussinger (2004) argue that government R&D subsidies have incentive impact on R&D inputs (government subsidies and other preferential policies encourage companies to increase R&D inputs), but also have a crowding-out effect (after being certified as high-tech enterprises, companies can obtain more government R&D subsidies which replace enterprise internal R&D expenditure). In our case, the empirical results indicate that companies do not significantly increase their R&D expenditure even if they obtain more government funding or tax credits. Therefore, the program is likely to have a limited effect on the promotion of independent innovation input, and may even cause a substitution effect or crowding-out effect on the independent innovation expenditure of a company.

Regarding the effect of the InnoCom program on the absorptive capacity

Table 4
Baseline results: 2SLS estimates for HNTE certification.

Dep. Var.	Innovation inputs				Absorptive capacity		Innovation outputs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lnGRD	*lnIRD*	*lnRDtotal*	*RDstaff*	*lnRDstock*	*HDstaff*	*lnHTInc*	*IIP*
T	1.962***	0.401	2.654**	−0.040	2.642**	−0.0260	2.939***	4.637***
	(0.264)	(0.844)	(1.356)	(0.032)	(1.296)	(0.141)	(0.264)	(0. 256)
Cons.	0.105	7.547***	5.186***	0.492***	1.046*	0.576***	0.800***	0. 198***
	(0.093)	(0.167)	(0.664)	(0.016)	(0.576)	(0.0631)	(0.204)	(0.010)
Obs	1725	1725	1725	1725	1725	1725	1725	1725

Robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

(H2), absorptive capacity can be an additional channel in enterprises' innovation outputs. The empirical findings suggest that being accredited as an HNTE will improve R&D capital stock while it has no significant effect on the number of highly educated staff members. Taken together, the total effect of the InnoCom program on absorptive capacity is positive.

From column (7) of Table 4, we can see the estimated coefficient of income associated with high-tech products is 2.939, which is significantly positive at the 1% level, meaning that the income of products (services) related to high-tech is expected to nearly triple after the company obtains high-tech certification. The last column of Table 4 show that the program has a significant positive impact on the number of independent intellectual property rights of enterprises, with a coefficient of 4.637, meaning that the number of IIPs increases on average > 4 times for firms receiving the preferential treatment.

Table 5 shows the results of OLS regression considering the influence of innovation inputs and absorptive capacity on innovation outputs, which is consistent with hypothesis H3 and H4. Together with, Table 4 has confirmed the effect of being accredited on the innovation inputs, absorptive capacity, and innovation outputs. It indicates that the innovation performance will be affected by the certification through both innovation inputs and absorptive capacity.

Fig. 3 shows a graphical analysis of the outcome variables as a local linear function of the score (score-70). Here, we focus on the effect of the accreditation on the internal R&D inputs and outputs. The figures give us visual evidence of a jump, which is weaker in the internal R&D inputs case. We can see that economic performance of innovation and the number of independent intellectual property rights have a significant jump around the threshold.

Table 5
Baseline results: OLS estimates for the impact of innovation inputs and absorptive capacity.

Dep. var.	*lnHTInc*	*IIP*
Innovation inputs		
lnRDtotal	0.357***	1.010***
	(0.034)	(0.113)
RDstaff	0.008***	−0.057***
	(0.003)	(0.011)
Absorptive capacity		
lnRDstock	−0.0339	0.460***
	(0.0350)	(0.116)
HDstaff	2.887***	0.137
	(0.306)	(1.012)
Cons.	−0.946***	−0.224
	(0.243)	(0.804)
Obs	1725	1725

Robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

We also try serval different window width to assess the stability of results. Table 6 shows the 2SLS estimation results of the policy impact on internal innovation inputs, high-tech income and innovation outputs in the current year considering sample windows of 20 and 10 scores around the cut-off. The signs and significance level of the coefficients do not differ in a significant way from the baseline results in Table 4, although the coefficients are larger with the sample window closer to the threshold, becoming a little less credible in the [65,75] sample. This is probably because the data size is much smaller when we estimate the jump using the sample very close to the cut-off. On the basis of the analysis above, we believe that the promotion effects of the policy on enterprise internal innovation inputs are not significant, but the policy play a very important role in boosting innovation outputs.

Table 7 reports the results of the policy's impact on internal innovation inputs and firm innovation outputs in 2013, 2014, and 2015. The first three columns of Table 5 report no significant increase in R&D investment by certified firms and the results confirm the existence of the crowding-out effect. Columns (4) and (5) report the increase in new and high technology products' (services') annual income. For the first two years after being certified, this increase is more than triple, which means that the impact on innovation output is sustainable, although the results are no longer significant after three years of being certified.

6.2. Robustness

In this section, we conduct five robustness checks to test the validity of our empirical design and the stability and reliability of our results, including RD random assumption test, jumps at non-discontinuity points test, involving covariates test, and classification regression test. We also use a difference-in-difference method based on propensity score matching (PSM + DID) to further test the robustness of the estimated results.

6.2.1. RD random assumption test

Another concern about regression discontinuity designs is the possibility that agents can perfectly control the running variable. Therefore, the treatment around the cut-off is as if it were not randomized, and the influence of the InnoCom program cannot be identified by the discontinuity of the outcome variable at the cut-off point (Hahn et al., 2001). Chen et al. (2018) use enterprise income tax records between 2008 and 2011 in China and find that firms can actually reclassify some expenditures as R&D to meet the minimum requirement for one category artificially.[11] To check whether similar bunching

[11] To qualify for the government program, firms are benchmarked on various attributes, one of which is current R&D expenditure: firms must spend a minimum amount on R&D to qualify, depending on their size. See more details in Table 1.

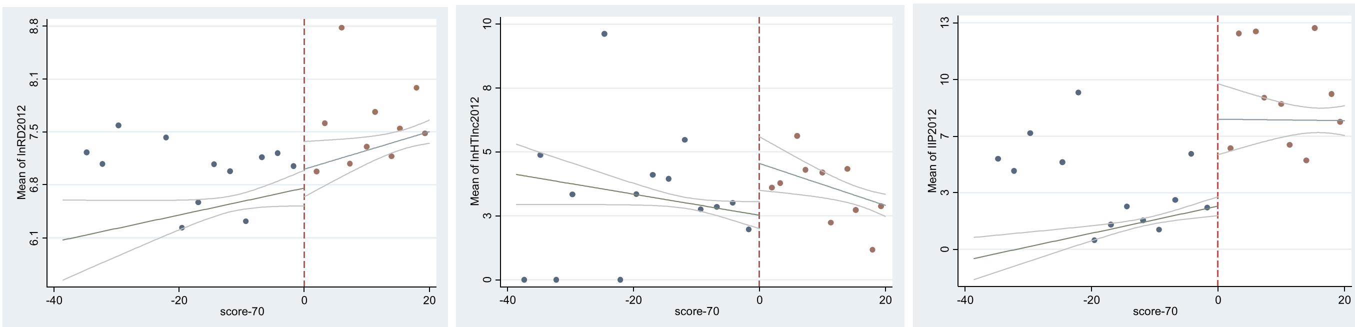

Fig. 3. Treatment period.
Notes: The x-axis variable is (actual score-70) and "0" is the cut-off. Y-axis variables are *lnIRD*, *lnHTInc*, *IIP* of 2012 respectively.

Table 6
Baseline results: 2SLS estimates for HNTE certification (changing window width).

Dep. var.	*lnIRD*		*lnHTInc*		*IIP*	
	[65,75]	[60,80]	[65,75]	[60,80]	[65,75]	[60,80]
T	0.401	1.306	4.484***	3.179**	4.959	3.837**
	(0.844)	(2.502)	(0.600)	(1.467)	(0.410)	(1.646)
Cons.	7.547***	6.838***	5.624***	1.886***	5.149	1.221*
	(0.167)	(1.501)	(0.197)	(0.404)	(0.71)	(0.718)
Obs	129	1063	129	1063	129	1063

Robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

patterns exist in our data, we follow Chen et al. (2018) by providing descriptive evidence. Fig. 4 plots the empirical distribution of the R&D intensity, the ratio of R&D staff and the ratio of staff with advanced degrees of Shanghai firms in 2012. The first panel of Fig. 4 shows the histogram of the overall R&D intensity distribution and the second panel plots the histogram of R&D intensity for small size firms. From the figures, we can see there are no clear bunching patterns at 3%, 4%, and 6% of R&D intensity, which corresponds to the three thresholds. Similarly, the other two figures present the distribution of human capital input requirements of HTNE certification and exhibit no clear bunching pattern. We think that in our case the assumption that individuals have imprecise control over the assignment variable holds, because the score is a comprehensive measure of four categories and it is rather unlikely that program participants can precisely control all requirements to just above the threshold.

6.2.2. Falsification tests

Another test involves estimating jumps at points where there should be continuous. The approach used here includes testing for a zero effect in settings where it should have no real effect (e.g., Imbens, 2004; Imbens and Lemieux, 2008). If the discontinuity in innovation performance detected for treated enterprises is caused by the InnoCom program, we should not observe any discontinuity in the absence of treatment. Here we use the dataset before the program (year 2011) and re-estimated the model for the company's internal R&D expenditure, economic performance of innovation and the number of independent intellectual property rights. Fig. 5 shows that before being certified there were no significant and positive jumps of the fitted functions around the threshold.

6.2.3. Tests involving covariates

As discussed above, Lee and Lemieux (2010) think that if the no-manipulation assumption holds, the unobserved factors between the treatment group and the control group should be similar in principle, so the estimated results should not be influenced by the decision whether or not to involve the covariates, no matter how highly correlated they are with the outcome variables. We directly include the covariates, after choosing a suitable order of polynomial. Based on previous literature (Zhou and Luo, 2005; Hirshleifer et al., 2011), combined with the practices of China, we consider the following factors that may affect innovation activities in technology companies as control variables: (1) Size of the company (*Size*), defined as the natural logarithm of the total assets of the company at the end of the year. (2) The debt ratio (*Leverage*), defined as total debt divided by total assets. (3) Return on assets (*ROA*), defined as profit divided by total assets. (4) Subsidy (*Subsidy*), defined as the natural logarithm of annual R&D subsidies from the government. (5) The ratio of employees worked in high-tech sectors to total number of employees (*RDstaff*).

Table 8 shows the effect of the program on the innovation performance of companies after adding control variables. We find that, after controlling the effect of annual R&D subsidies from the government, the signs and significance level of the coefficients of innovation outputs do not differ although the coefficients are slightly lower than those without

Table 7
Baseline results: 2SLS estimates for HNTEs certification (in the long run).

Dep. Var.	*lnIRD*			*lnHTInc*			*IIP*		
	2013	2014	2015	2013	2014	2015	2013	2014	2015
T	0.223	0.305	1.103	3.205***	1.888***	1.891	2.489***	1.976***	1.659***
	(1.701)	(1.552)	(1.884)	(0.527)	(0. 687)	(3.536)	(0.587)	(0.168)	(0.194)
Cons.	7.113***	7.238***	6.928***	4.731***	4.804***	6.533***	0.508*	0.865***	0.969***
	(0.747)	(0.853)	(0.974)	(0.216)	(0.298)	(2.165)	(0.270)	(0.039)	(0.051)
Obs	1140	1107	830	1140	1107	830	1140	1107	830

Robust standard errors in parentheses.
** $p < 0.05$.
* $p < 0.10$.
*** $p < 0.01$.

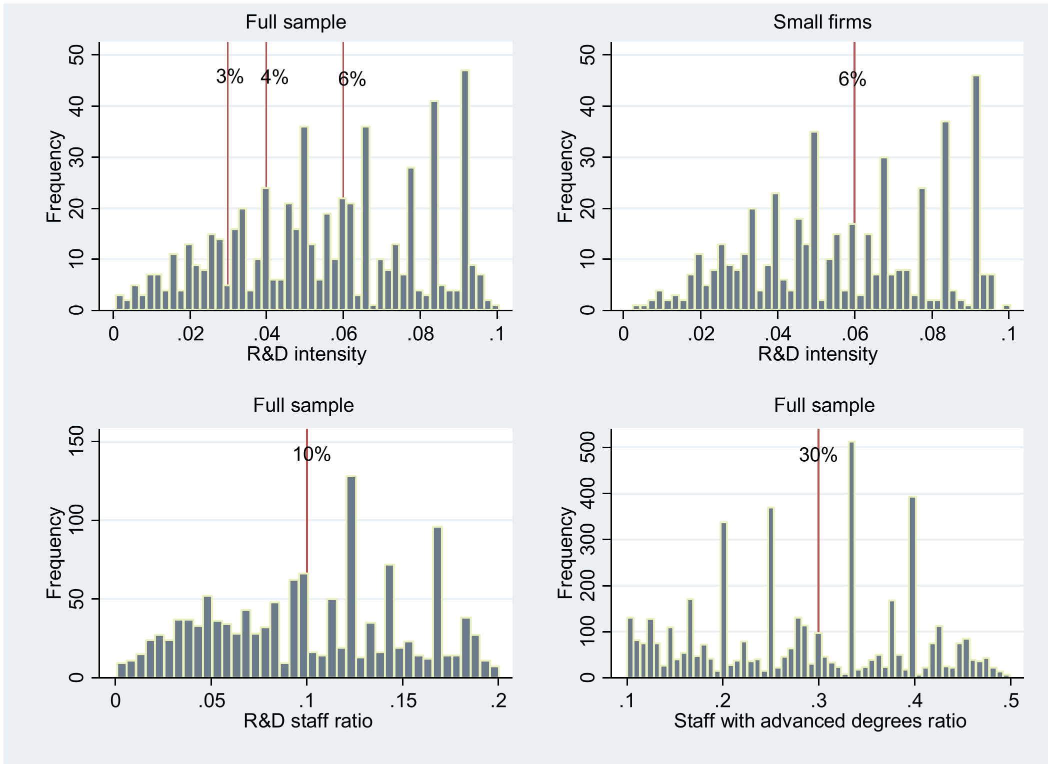

Fig. 4. Robustness of bunching tests.
Notes: The first two figures plot the empirical distribution of R&D intensity for all sizes of firm and only small firms that have R&D intensity between 0.5% and 10%. The other two figures report the proportions of R&D staff and staff with advanced degrees of the total number of employees, respectively. Note that the red lines are the thresholds that qualify a company to apply for InnoCom certification. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

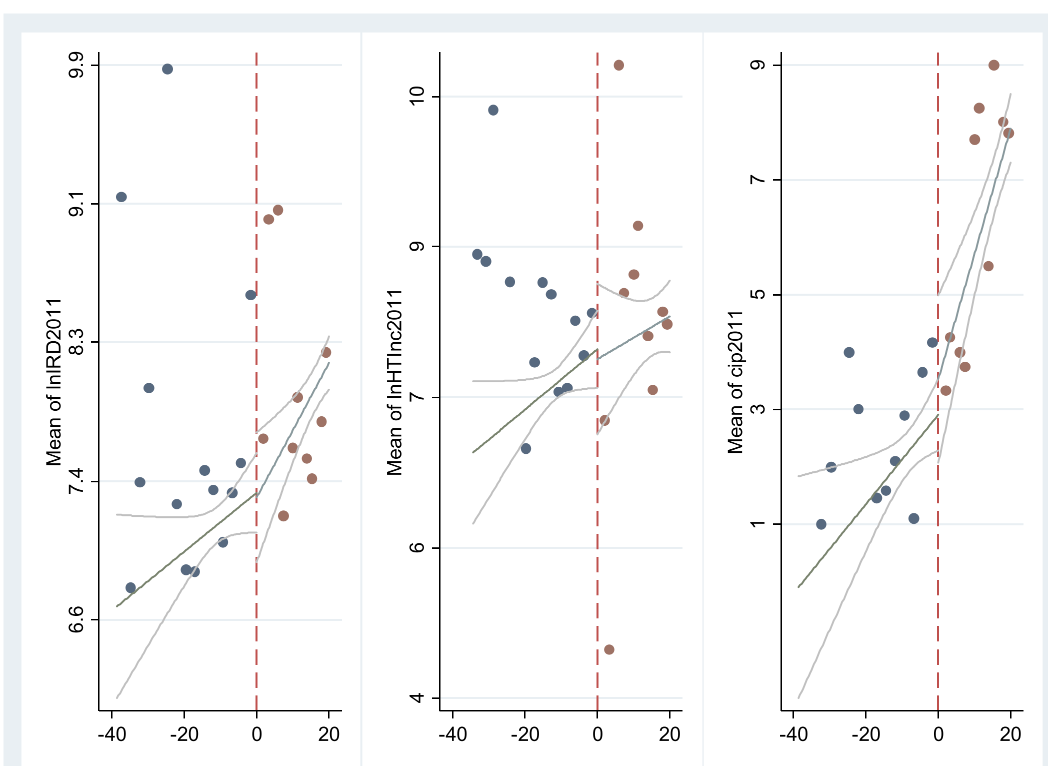

Fig. 5. Pre-treatment period.
Notes: The x-axis variable is (actual score-70) and "0" is the cut-off. Y-axis variables are *lnIRD, lnHTInc, IIP* of 2011 respectively.

Table 8
Robustness: Add control variables.

Dep. var.	(1)	(2)	(3)
	lnIRD	*lnHTInc*	*IIP*
T	0.885*	1.595***	3.965***
	(0.493)	(0.293)	(0.273)
Size	0. 731***	0.126***	0.011
	(0.073)	(0.014)	(0.008)
Leverage	0.015**	0.003	0.0001
	(0.006)	(0.002)	(0.001)
ROA	−0.034**	−0.004	−0.0004
	(0.015)	(0.003)	(0.001)
Subsidy	0.124***	0.108***	0.108***
	(0.019)	(0.031)	(0.023)
RDstaff	4.174***	2.377***	0.927***
	(0.206)	(0.094)	(0.046)
Cons.	−3.016***	−0.482***	−0.035
	(0.430)	(0.099)	(0.055)
Obs	1634	1634	1634
R^2	0.582	0.121	0.213

Robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

control variables (Table 4). It indicates that there are some other instruments at work besides subsidy. There is some evidence of a slight difference in the R&D input, but only at the 10 percent level. We interpret these results as further evidence of the positive influence of the InnoCom program.

6.2.4. Classification regression test

There may be differences in the innovation performance of enterprises with different types of ownership (Wu, 2012). The response to incentive policies is also different. The relationship between enterprise ownership and innovation performance in the process of economic transition in China is of particular concern. State-owned enterprises and non-state-owned enterprises have their own advantages and disadvantages in terms of technological innovation. Most state-owned enterprises are powerful and have sufficient R&D funds. Non-state-owned enterprises have a higher awareness of market competition and more incentive to innovate to gain competitive advantage. Therefore, the policy may have different influences on innovation performance of different types of enterprise.

Table 9 reports the impact of the program on high-tech income of different types of company. Although the estimation coefficients of different types of company are different, they are all significantly > 0, indicating that the policy has increased the income related to high-tech products. And the promotion effects on joint stock companies, state-owned enterprises and HMT solely owned companies are the most significant.

Table 9
Robustness: classification regression test for high-tech income.

	Coeff.	s.e.	T value	*P* value	R^2
State-owned enterprise	2.895	1.178	2.460	0.016	0.11
Joint stock company	4.237	1.621	2.610	0.010	0.12
Limited liability company	2.493	0.138	18.090	0.000	0.07
Company limited by shares	1.342	0.531	2.530	0.014	0.14
Private limited liability company	2.364	0.345	6.840	0.000	0.08
Joint venture of mainland and HMT	1.660	0.763	2.180	0.033	0.06
HMT solely owned	2.539	0.633	4.010	0.000	0.09
Sino-foreign joint venture	1.227	0.421	2.920	0.004	0.08
Foreign-funded enterprise	0.942	0.535	1.760	0.079	0.03

Notes: HMT is an acronym for Hong Kong, Macau and Taiwan. The dependent variable in Table 9 is the logarithm of the company's annual new and high-tech product (service) revenue.

6.2.5. Difference-in-differences

By 2015, a total of 6071 companies in Shanghai were recognized as high-tech enterprises,[12] which provides a good quasi-natural experiment to use the difference-in-difference method. Specifically, in our sample, enterprises that have been certified as HNTEs constitute a treatment group, and the rest of the enterprises that did not obtain certification naturally make up the control group. To maintain the consistency of the research, we still study the impact of the policy on enterprises that were certified as HNTEs in 2012. The time window includes each year before and after, so the time span is from 2011 to 2013. Thus, we estimate the following DID equation over the samples:

$$Y_{it} = \beta_0 + \beta_1 HT_i * Year_t + \beta_2 X_{it} + \gamma_t + \mu_i + \varepsilon_{it} \tag{5}$$

where Y_{it} is the outcome variable and X_{it} is a vector of multiple control variables for firm *i* at period *t*. In keeping with the prior setting, we still choose *Size*, *Leverage*, *ROA*, *Subsidy* and *RDstaff* as the control variables. $Year_t$ is a dummy variable equal to 1 in the treatment period and zero otherwise. HT_i is a treatment variable equal to one if the enterprise is HNTE and zero otherwise. γ_t is the year fixed effect and μ_i is the individual fixed effect. The coefficient of interest is β_1, which is the product of two dummies and which is equal to one for those individuals in the treatment group in the treatment period. It measures the impact of the program on the company's innovation performance. If innovative policy really improves innovation performance, then β_1 should be significantly positive.

The first three columns of Table 10 show the estimation results of DID. In column (1), unlike the results of fuzzy regression discontinuity estimation, the coefficient of interest for the R&D investment (0.154) indicates a significant difference between the control group and the treatment group at the 5% level. This positive coefficient implies that the innovation input of HNTEs is higher than that non-HNTEs. Similarly, in column (2), the coefficient for new and high technology products (services) income (2.914) indicates a significantly positive difference between the treatment group and the control group at the 1% level and the same for the number of independent intellectual property rights. Therefore, innovation performance of HNTEs is higher than that non-HNTEs.

The different results from fuzzy regression discontinuity and DID estimation also support our view that there may be selection bias if we use traditional methods. Therefore, we try to resolve this problem by combining propensity score matching (PSM) with DID methods. Specifically, the propensity score can be used to match units in the common support or overlap across the treatment and control samples, and the treatment effect is calculated across participants and matched control units within the overlap. Hirano et al. (2003) show that the estimator of a weighted least squares regression is fully efficient where the weights of the control observations are assigned according to their propensity score. Columns (4)–(9) show similar results compared with the FRD estimation. However, the interaction term of the R&D investment is positive, but not statistically significant. The results show that the impact of the program is significantly positive on innovation outputs, but it is weaker, though positive, on R&D investment.

7. Conclusions

Although China has become used to supercharged rates of expansion, its economy still faces many challenges with a lack of enterprise innovation and an imbalance of the industrial structure. This paper evaluates the influence of the InnoCom program on innovation activities of new and high-tech firms based on survey data of Shanghai's scientific and technological enterprises from 2011 to 2015. We exploit the mechanism of the program to apply an IV/RD parameter estimation

[12] Data source: http://www.shanghai.gov.cn/nw2/nw2314/nw2318/nw26434/u21aw1109178.html

Table 10
Robustness: DID and PSM + DID estimation.

	DID			PSM + DID					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. var.	*lnIRD*	*lnHTInc*	*IIP*	*lnIRD*	*lnIRD*	*lnHTInc*	*lnHTInc*	*IIP*	*IIP*
HT ∗ year	0.154**	2.914***	1.430***	0.049	0.122	2.160***	2.242***	4.013***	3.822***
	(0.062)	(0.160)	(0.412)	(0.060)	(0.087)	(0.205)	(0.201)	(0.446)	(0.458)
Size	0.422***	0.798***	0.569***		0.516***		0.811***		0.494**
	(0.027)	(0.071)	(0.182)		(0.037)		(0.079)		(0.194)
Leverage	9.80E-07	−2.11E-05	−2.26E-05		−1.36E-06		−1.74E-05		−2.43E-05
	(9.59E-06)	(2.47E-05)	(6.35E-05)		(1.06E-05)		(2.26E-05)		(5.61E-05)
ROA	−0.012	−0.006	−0.019		−0.023**		0.001		−0.019
	(0.007)	(0.019)	(0.049)		(0.011)		(0.024)		(0.060)
Subsidy	0.078***	0.0378	0.075		0.106***		0.113***		0.180**
	(0.009)	(0.024)	(0.061)		(0.015)		(0.032)		(0.080)
RDstaff	5.211***	3.036***	0.550		6.106***		3.957***		0.842*
	(0.076)	(0.195)	(0.501)		(0.094)		(0.206)		(0.497)
Cons.	−0.722***	−6.668***	−1.863	3.836***	−2.194***	2.351***	−5.842***	2.618***	−2.01
	(0.252)	(0.650)	(1.670)	(0.038)	(0.317)	(0.062)	(0.676)	(0.098)	(1.671)
Time fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs	15,921	15,921	15,921	10,293	10,051	10,293	10,051	10,293	10,051
R^2	0.380	0.157	0.008	0.076	0.413	0.082	0.152	0.013	0.014

Robust standard errors are clustered by firms.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

method under a fuzzy discontinuity regression design framework to deal with the endogeneity problem in the regressions. In addition, we look at the impact of the InnoCom program on both innovation input and innovation output.

We find that the InnoCom program has a positive effect on the innovative output of HNTEs, including high-tech product revenues and independent intellectual property rights, which is consistent with the results using the DID method based on propensity score matching. Another effect of the policy is insignificant impact on corporate internal innovation investment. The reason might be that Government subsidies are likely to have a crowding-out effect on a company's internal innovation investment. The results of high-tech product revenues and independent intellectual property rights, read jointly, suggest that the increase in innovation outputs is a consequence of two main channels: the increase of a firm's total innovation inputs and the improvement of absorptive capacity. In addition, we estimate the impact for another three years after the determination, and it turns out that the certification has a sustained impact on innovation output.

Despite the effort in developing a unified framework and estimating the relationships between policy instruments and firms' innovation performance, further robustness tests are needed. More specifically, the variables that should not be affected by the determination system are continuous around the breakpoint and the assignment variable cannot be precisely manipulated. The counterfactual test shows no positive discontinuities of the functions around the cut-off over the pre-treatment period (before the program). After involving control variables, the coefficients of the high-tech products' (services') income and the number of independent intellectual property rights are slightly lower than those without control variables, but the signs and significance level do not differ in a significant way. These results are robust to the sensitivity exercise after considering the heterogeneity of the ownership of enterprises, and are also confirmed by combining PSM with DID methods, proving stability and reliability.

7.1. Practical and policy-making implications

The results provide useful insights into promoting innovation performance. Based on the findings above, combined with innovation environment in China, this paper brings forward the following related policy suggestions.

First, although China has introduced many innovation incentive policies, it has not yet formed a set of mature and effective mechanisms for Chinese enterprises, and the incentive effect of the InnoCom program on enterprise internal innovation input is still not significant. When design the system, policymakers should not only adhere to a high certification threshold, but also strengthen the follow-up supervision of enterprise activities, and put forward higher requirements on the R&D investment, human capital input, new product sales and patent acquisition after enterprise certification. At the same time, in the implementation of the system, more effective subsidy policies should be considered to guide enterprises to increase effective innovation input.

Second, from the perspective of policy intensity, all enterprises that passed the certification can get basically the same preferential benefit, and the one-size-fits-all approach is not reasonable. Different preferential policies should be given to different enterprises and industries according to different investment and output levels in research and development.

7.2. Limitations and future research

Of course, our study has a number of caveats. First, we only consider Shanghai as an example. This is a common disadvantage of regression discontinuity that the interval validity is strong, but the external validity is questionable. We do not claim that our results hold for other regions or for China as a whole, but our empirical method can be directly applied to evaluate the policy effect. Second, on January 29, 2016, the relevant departments revised the *Guidelines* which had been in place for eight years. It is possible that what we have found might only be partially valid for the year before the new policy was implemented. We leave these issues for future research.

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Appendix A. Theoretical relationship between policy instruments and R&D inputs

This section develops and discusses a simple and stylized model of innovation investment whereby firms respond to three preferential policies. In this model, firms engage in an optimal level of research input (which includes both unskilled labor but also human capital input). The amount of research input is related to the firm's costs, which in turn increases the success probability of innovation. This model yields the following intuitive result: a decrease in the company's cost of research increases the amount of R&D input in equilibrium and if the firm inputs more, it will have a higher probability of making higher profits. Before considering how the InnoCom program impacts a company's research input choices, we first consider a setup with no such government program.

A.1. R&D activity

To simplify the analysis, we make the following two assumptions:

Assumption 1. There is no material capital input in R&D activities (Romer, 1990). R&D activities require not only unskilled labor but also human capital input (skilled labor). Although the two cannot be separated completely, we separate them in order to clarify the different roles of the two types of labor input in R&D activities.

Assumption 2. There is no memory in the technology: the innovation process depends only upon the current flow of input to research rather than past research.

In addition, we do not distinguish different forms of innovation and types of product, which avoids complex discussions on the various forms of innovation and different trading behaviors, since this is not the main focus of our analysis.

R&D activity produces a random sequence of innovations. The success rate of innovations I is $\phi(I)$ in Eq. (1),[13]

$$\phi(I) = \phi(\ln(AL^{\alpha}H^{1-\alpha})) = \phi(lnA + \alpha lnL + (1-\alpha)lnH),\ 0 < \alpha < 0.5 \tag{1}$$

where ϕ is a cdf function, so it is between zero and one and increasing with I, L and H are the flows of unskilled and skilled labor used in R&D, A and α are positive constant parameters, and the function of innovation is in the form of Cobb-Douglas (An et al., 2009). Actually, α can be any constant (Cassiman et al., 2002; Morales, 2004). We set α to fulfill the $\alpha < 0.5$ condition in the function just to highlight the importance of skilled labor. In theory, the marginal gain from one unit of skilled labor is more than that from one unit of unskilled labor.

A.2. Production

The product is produced using the fixed quantity K of physical capital, and the production function can be written as:

$$Y = F(L, H, K). \tag{2}$$

We consider two types of firm: innovation leaders and followers. For convenience, we set a unit marginal cost of the innovation leader through time (Davidson and Segerstrom, 2000), and we set the marginal cost of followers as c, $c > 1$. When technology diffusion has not reached the level that other companies can imitate, innovating companies have absolute pricing power in the market, and followers cannot obtain excess profits. Therefore, the leader can set the price at the level of c, which is the lowest price that the followers can accept. Thus, the leader earns the profit flow:

$$R = \frac{(c-1)}{c}\theta C,\ 0 < \theta < 1, \tag{3}$$

where C is the total spending of consumers and θ is the market share of the innovation leader. The reason why the leader does not set prices higher than c, is that the leader company cannot completely occupy the entire market with the constraints of expansion barriers of the company's products, consumer cognitive delay and other factors. Instead of spending a lot of fixed costs to occupy unfamiliar new markets, companies prefer patent fees, similar to the market's franchises and chain operation models. Besides, the patents of the leader company have a period of validity, and that is why followers are willing to operate without profits at this stage.

The objective of the leader is to maximize the expected present value of profits over the current interval. The firm's value function takes the form:

$$V = \int_0^{\tilde{t}} e^{-rt}\phi(I)Rdt = \frac{\phi(I)R}{r}(1 - e^{-r\tilde{t}}), \tag{4}$$

where r is the discount rate and $\tilde{t}$ is the length of time that the company controls the market after the success of innovation. Eq. (4) identifies V as the future flow of output discounted at the fixed rate r.

A.3. Firms' maximization problem

Assume there are no contemporaneous spillovers in the research process (Aghion and Howitt, 1992), that is, a firm employing the amounts L and H of the two factors in R&D will achieve innovations with a probability of $\phi(I)$, independently of the input of other companies. By (4) and Assumption 1, the objective of a firm in choosing L and H is to maximize the flow of expected profits from R&D:

[13] There are no contemporaneous spillovers in R&D activities, that the probability is independent of the inputs of other firms. Note that $\phi'(I) > 0$, $\phi''(I) \le 0$.

$$\max[V - (w_L L + w_H H)], \tag{5}$$

where w_L and w_H are the wages of common labor and specialized human capital, respectively, and $w_L < w_H$. The first-order condition of profit maximization with respect to L and H, together with Eq. (1) produces:

$$\frac{\partial V}{\partial L} = \frac{(1 - e^{-r\tilde{t}})R\phi'(I)\alpha}{rL} = w_L \text{ and } \frac{\partial V}{\partial H} = \frac{(1 - e^{-r\tilde{t}})R\phi'(I)(1 - \alpha)}{rH} = w_H. \tag{6}$$

From this, we can calculate the optimal level of innovation input without any favorable policy:

$$L^* = \frac{(1 - e^{-r\tilde{t}})R\phi'(I)\alpha}{rw_L} \text{ and } H^* = \frac{(1 - e^{-r\tilde{t}})R\phi'(I)(1 - \alpha)}{rw_H}. \tag{7}$$

The model reflects the reality that the major uncertainty of research activities from the company's perspective is the high risk of failure. We use the literature on innovation arrival rate and incentive forms to argue that input scale also impacts the risk. Although our model is based on previous literature, we exploit the rich differences in the forms of policy instruments particular to high-tech enterprises. As introduced in the background, we consider three types of policy instruments (R&D cost deductions, R&D funding, and tax credits) separately.

A.3.1. R&D cost deductions

Local administrators give different proportions of R&D cost reductions to the qualified companies, and then the problem of maximizing the profits of R&D activities for innovative companies is:

$$\max[V - (1 - s)(w_L L + w_H H)], \tag{8}$$

where s is the ratio of R&D expense subsidies given by policy makers to companies, and $0 < s < 1$. The enterprise maximizes profits through choosing optimal labor and human capital investment, so we derive:

$$L^*_{RCD} = \frac{(1 - e^{-r\tilde{t}})R\phi'(I)\alpha}{r(1 - s)w_L} \text{ and } H^*_{RCD} = \frac{(1 - e^{-r\tilde{t}})R\phi'(I)(1 - \alpha)}{r(1 - s)w_H}. \tag{9}$$

Since $0 < s < 1$, we have $L^*_{RCD} > L^*$ and $H^*_{RCD} > H^*$. R&D cost reductions encourage firms to input more into R&D. According to Eq. (9), an increase in the degree of R&D cost deductions increases the stationary equilibrium amount of labor input L and human capital input H. According to Eqs. (1) and (4), given fixed values of the parameters A and α, the increase of labor and human capital will also bring higher innovation success probability and hence higher enterprise value.

7.2.1. R&D funding

Another favorable policy is government R&D funding. Assume the firm receives a subsidy of S for its R&D projects, in which $\mathrm{a} \cdot \mathrm{S}$ is used to increase the labor input, and $(1 - \mathrm{a}) \cdot \mathrm{S}$ is used to increase human capital investment. The new investments in labor and human capital of the enterprise are:

$$\tilde{L} = L + \frac{aS}{w_L} \text{ and } \tilde{H} = H + \frac{(1 - \mathrm{a})S}{w_H}. \tag{10}$$

The new rate of innovation becomes:

$$\phi(\tilde{I}) = \phi(\ln(A\tilde{L}^{\alpha}\tilde{H}^{1-\alpha})) = \phi(lnA + \alpha ln\tilde{L} + (1 - \alpha)\ln\tilde{H}). \tag{11}$$

The firm chooses L and H to maximize its profit:

$$\max[\tilde{V} - (w_L\tilde{L} + w_H\tilde{H}) + S]. \tag{12}$$

Using similar reasoning, the corresponding first-order condition of maximizing expected profits in R&D races are:

$$\frac{\partial\tilde{V}}{\partial L} = \frac{(1 - e^{-r\tilde{t}})\phi'(I)R\alpha}{r\left(L + \frac{\mathrm{Sa}}{w_L}\right)} = w_L \text{ and } \frac{\partial\tilde{V}}{\partial H} = \frac{(1 - e^{-r\tilde{t}})\phi'(I)R(1 - \alpha)}{r\left(H + \frac{S(1-\mathrm{a})}{w_H}\right)} = w_H. \tag{13}$$

The enterprise internal inputs are given by

$$L = \frac{(1 - e^{-r\tilde{t}})\phi'(I)R\alpha - r\mathrm{Sa}}{rw_L} \text{ and } H = \frac{(1 - e^{-r\tilde{t}})\phi'(I)R(1 - \alpha) - rS(1 - \mathrm{a})}{rw_H}. \tag{14}$$

Putting the last two equations into Eq. (10), the number of total investments after receiving subsidies will be

$$\tilde{L} = L + \frac{\mathrm{Sa}}{w_L} = \frac{(1 - e^{-r\tilde{t}})\phi'(I)R\alpha - r\mathrm{Sa} + r\mathrm{Sa}}{rw_L} = \frac{(1 - e^{-r\tilde{t}})\phi'(I)R\alpha}{rw_L}, \tag{15}$$

$$\tilde{H} = H + \frac{S(1 - \mathrm{a})}{w_H} = \frac{(1 - e^{-r\tilde{t}})\phi'(I)R(1 - \alpha) - rS(1 - \mathrm{a}) + rS(1 - \mathrm{a})}{rw_L}$$

$$= \frac{(1 - e^{-r\tilde{t}})\phi'(I)(1 - \alpha)}{rw_L}. \tag{16}$$

Higher innovative R&D subsidy S leads to lower enterprise internal research input, whereas the number of total investments stays the same. It is worth noting that direct government subsidies generate a complete crowding-out effect, that is, firms will use government funds to replace enterprise internal R&D investment.

A.3.2. Tax credits

Drawback schemes allow qualified firms to enjoy a lower average tax rate. We assume the firm faces a tax credit Δ and write the expected value as follows:

$$V = \int_0^{\tilde{t}} e^{-rt}\phi(I)Rdt = \frac{\phi(I)R}{r(1-\Delta)}(1-e^{-r\tilde{t}}). \tag{17}$$

The firm aims to maximize profit by choosing L and H. The optimization problem is

$$\max[V-(w_L L + w_H H)]. \tag{18}$$

The optimal level of research input L^* and H^* satisfies the conditions

$$\frac{\partial V}{\partial L} = \frac{(1-e^{-r\tilde{t}})\phi'(I)R\alpha}{rL(1-\Delta)} = w_L \text{ and } \frac{\partial V}{\partial H} = \frac{(1-e^{-r\tilde{t}})\phi'(I)R(1-\alpha)}{rH(1-\Delta)} = w_H. \tag{19}$$

The inputs can be expressed as

$$L^*_{tax} = \frac{(1-e^{-r\tilde{t}})\phi'(I)R\alpha}{r(1-\Delta)w_L} \text{ and } H^*_{tax} = \frac{(1-e^{-r\tilde{t}})\phi'(I)R(1-\alpha)}{r(1-\Delta)w_H}. \tag{20}$$

Since $0 < s < 1$, we have $L^*_{tax} > L^*$ and $L^*_{tax} > H^*$. Note that for both types of R&D investment, the profit-maximizing input of R&D effort is an increasing function of tax credits, and the increase of labor and human capital also increases innovation success probability and enterprise value.

In short, for the proportional R&D cost deductions, the government will provide a certain percentage of R&D expenses to cover the costs of projects. Unlike direct subsidies, companies need to invest a certain amount of money before they receive the corresponding proportion of subsidy. These features make policies more likely to generate positive incentive effects; the more capital that companies invest, the more subsidies they receive. The incentive mechanism of tax credits is similar to proportional R&D cost deductions, as both require companies to invest in advance to get preferential treatment.

Unlike the discussion above, there are ample negative incentive effects related to public funding. Scholars have obtained evidence of crowding-out effects through theoretical models and empirical studies. For example, Wallsten (2000) finds that the government funding of firms' R&D will totally squeeze out business R&D expenditure by using a U.S. sample. David et al. (2000) review literature about government-funded R&D and find that about one-third of the literature supports the crowding-out effect of government public funding of R&D.

One form of crowding-out is that enterprises could have invested in the projects with higher success probabilities and high private rates of return by using either internal or external funds, suggesting that the research grants are in fact unnecessary and may be crowding out private investments (Lach, 2002). The subsidy is "crowding out" an investment that would otherwise be firm expenditure because government subsidies reduce R&D risks and capital costs (Lee and Cin, 2010). Companies can transfer some of their own funds from projects that are profitable but risky to productive areas after receiving subsidies, so that they can use less funds to obtain project benefits and avoid risks, which in turn produces the crowding-out effect.

In summary, we argue that the principle and means of the preferential policy affect the optimal level of research activity input, which in turn influences the flow of profits. Specifically, based on our stylized model and the discussions above, we put forward the following two theoretical claims: First, an increase in the R&D cost deductions and tax credits increases the stationary equilibrium amount of research input, which will also bring about higher probability of innovation and increase the enterprise value. Second, direct government funding generates a crowding-out effect, that is, firms will use government funds to replace enterprise internal R&D investment. Note that the three preferential policies have different effects on innovation input and output. Therefore, the ultimate effect of the determination of HNTEs is still uncertain and needs further verification in the empirical part.

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