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Asian Journal of Technology Innovation

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rajt20

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To cite this article: Shougui Luo & Yahui Sun (2020) Do Selective R&D incentives from the Government promote substantive innovation? Evidence from Shanghai technological enterprises, Asian Journal of Technology Innovation, 28:3, 323-342, DOI: 10.1080/19761597.2020.1758586

To link to this article: https://doi.org/10.1080/19761597.2020.1758586

Published online: 29 Apr 2020.

ASIAN JOURNAL OF TECHNOLOGY INNOVATION
2020, VOL. 28, NO. 3, 323–342
https://doi.org/10.1080/19761597.2020.1758586

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Do Selective R&D incentives from the Government promote substantive innovation? Evidence from Shanghai technological enterprises

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ABSTRACT

Some types of government R&D incentives, such as subsidies and the High-and-New Technology Enterprise (HNTE) programme in China, are considered selective because they are given to few eligible firms. The selection process necessitates firm signalling and thus may influence R&D activities before the policy takes effect. This paper explores the innovation behaviour of firms in both the period of preparing to apply for the incentives (application period) and the period after obtaining the incentives (execution period). The empirical results show that subsidy programmes can effectively encourage firms to carry out substantive innovation, while HNTE programme stimulates deceptive innovation in the application period and suppresses innovation motivation in the execution period. This result implies that the HNTE programme fails, at least in the short run, to drive substantive innovation. Comparison of the two policies also shows that information gathering and inspection may reduce firm deviation.

KEYWORDS
Selective R&D incentive; substantive innovation; deceptive innovation; imperfect information; application period

JEL
L53; O31; O38

1. Introduction

It has been widely agreed that the externalities, indivisibilities and uncertainties of innovation activities will inevitably lead to market failure, which prevents firms from achieving the socially optimal level of spontaneous R&D activities (Arrow, 1972). To encourage high-quality R&D projects and the efficient utilisation of innovation resources, selective R&D incentives are adopted worldwide (OECD, 2010). Selective R&D incentives are R&D policies that allow the government to provide fiscal support to qualified R&D projects or firms. The use of a selective procedure implies that the policy does not indiscriminately cover all firms. However, since the government cannot supervise the R&D activities of all applicants, there is a possibility of adverse selection and moral hazard, which means the government may fail to select qualified firms and firms may not innovate as they promise.

A growing body of literature provides evidence for such government failure and firm deviation. Studies show that in addition to 'substantive innovation', which aims to improve productivity and gain a competitive advantage, firms may engage in 'deceptive

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innovation', which aims to disguise a firm's real innovation capacity to meet other objectives, such as catering to the government (Hu et al., 2017; Li & Zheng, 2016). For example, since it is difficult to value R&D output, some firms may carry out a large number of low-quality R&D projects as a signal that they are highly innovative, and the government can hardly distinguish such firms from truly innovative ones (An et al., 2009).

In the growing literature, most studies focus on firms' activities after they obtain innovation resources; however, from the moment a firm decides to apply for the incentive, its behaviour changes. Firms may schedule their innovation activities in advance to comply with the government's preferences, thereby improving their chances of success (Shaffer, 1995). However, a problem arises if such innovation activities do not result in technological progress. If the firm's only purpose is to embellish its innovation capability (i.e. the firm is conducting deceptive innovation), then such innovation activities can result in misallocation of public resources. This possibility also suggests that a selective R&D incentive may distort firms' innovation behaviour before it takes effect. However, we have found few studies on this topic.[1]

This paper explores the role of selective innovation incentives from two dimensions: the time dimension and the policy dimension. We consider both the period during which enterprises prepare their applications (application period) and the period when the incentive takes effect (execution period). We also compare two policies with different degrees of imperfect information: the direct subsidy policy and the High-and-New Technology Enterprise (HNTE) Program in China. The former requires detailed information on specific R&D projects in both periods, while the latter focuses only on the firm innovation achievement in the application period and performs limited supervision. We use panel data on Shanghai technological enterprises from 2008 to 2016 with more than ten thousand observations each year. To solve the problem of selection bias, the IV method is used in the main regression, and the conditional difference-in-difference (CDID) method is employed as a robustness check.

The remainder of this paper is structured as follows: In Section 2, we provide the theoretical background, including a brief introduction to China's subsidy policy and the HNTE programme. Section 3 describes the data, and Section 4 describes the empirical model. The empirical results are provided in Section 5, and Section 6 provides robustness checks. Finally, Section 7 concludes the paper.

2. Theoretical background

2.1. Backgrounds of selective R&D incentives in Shanghai

There is a comprehensive category of subsidy programmes available to firms in Shanghai, including national- and local-level project-based grants, local grants for specific technologies or industries, and grants from other sources. Various subsidy programmes are designed with different sizes, durations and target firms, but they usually share the same application procedure. Figure 1(a) shows the general timeline of subsidy programmes. The government announces its subsidy plan and screening criteria at period t_{s1}, which usually requires applicants to provide detailed descriptions of their projects, including their aim, feasibility, schedule and budget. Then, at period t_{s2}, firms develop R&D projects according to the subsidy plan and submit their application. At period t_{s3},

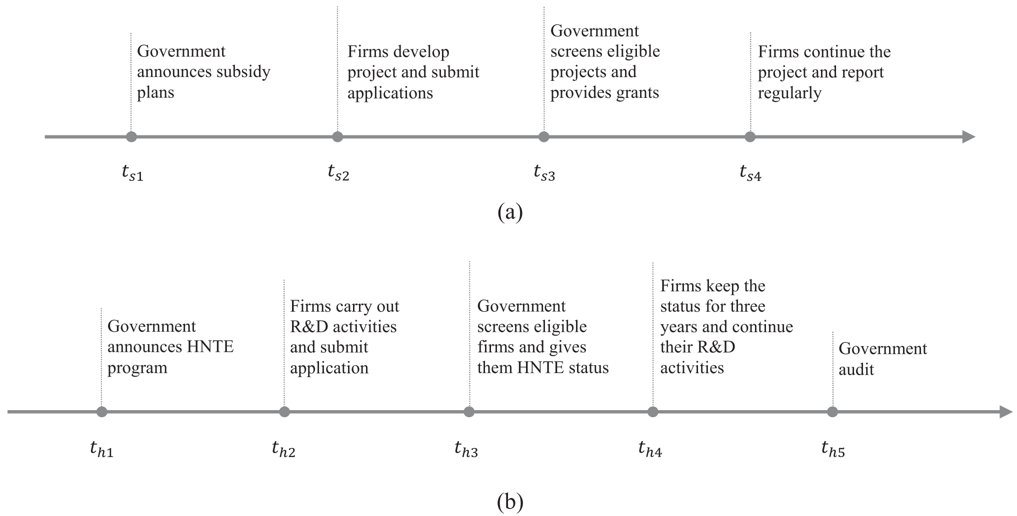

Figure 1. (a) Timeline of subsidy programmes and (b) Timeline of HNTE programme.

the government chooses highly innovative projects with high social value among numerous applicants according to its plan and provides grants to the selected projects. Finally, at period t_{s4}, the subsidised firms continue their R&D projects and regularly report their progress and use of resources.

In contrast to direct subsidies, the HNTE programme is a tax-based incentive that mainly considers the existing innovation achievements of firms. As shown in Figure 1 (b), the timeline also starts with the announcement of a project plan and screening criteria at period t_{h1}. Firms then prepare themselves and submit the application at period t_{h2}. Subsequently, the government chooses qualified applicants that meet the predetermined standards and have high innovation capabilities at period t_{h3}. The screening is achieved by scoring the innovation capability of applicants. This evaluation includes four main aspects: intellectual property rights (30 points), ability to transfer the R&D outputs into economic profits (30 points), ability to organise and conduct R&D activities (20 points) and potential for further development (20 points).[2] At period t_{h4}, the chosen firms are awarded HNTE status for three years (Jia & Ma, 2017) and continue their R&D activities. HNTEs are provided with support in terms of taxes, human resources, capital and many other aspects, including a 15% corporate income tax reduction compared with the overall tax rate of 25% and preferential policies for talent introduction and specific subsidies. Finally, at period t_h5, firms are audited by the government to determine whether to retain their HNTE status for the next three years. We would like to highlight that the audit of HNTEs occurs at the end of the third year, i.e. $t_{h5} - t_{h4} = 3$, and firms are not inspected before the audit. This supervision mechanism is different from subsidy programmes and may have different impacts on policy effectiveness.

2.2. Literature Review

The market failures caused by knowledge spillover and the information asymmetry of the capital market lead to a shortage of private R&D, which provides the theoretical rationale for public intervention (Dimos & Pugh, 2016). Direct subsidies and tax incentives are the two main R&D policy instruments used by countries around the world (Busom et al., 2014) and thus have consistently been the focus of scholars. The government shares the R&D costs and risks with firms through financial support, which increases the expected return of the per unit R&D cost of firms. As a result, firms are stimulated to perform more innovation activities (Lee & Cin, 2010). Receiving R&D subsidies could be a signal of strong innovation ability, which helps firms raise funds and alleviate the financial constraints of R&D projects (Takalo & Tanayama, 2010). Subsidies increase firms' total R&D expenditure and thus promote their R&D achievement. Dimos and Pugh (2016) investigated 239 estimates of the effect of subsidies on firms' innovation output and found that only 9 estimates suggested an over-full crowing out effect while 152 estimates justified the promoting effect.

Various studies indicate that tax reduction drives firm innovation, which provides a theoretical basis for HNTE programmes. Tax preferences alleviate the financing constraints of firms and enable them to invest more resources into new R&D activities without distorting their innovation decisions (Czarnitzki et al., 2011; Myers & Majluf, 1984). Research on the price elasticity of R&D demand shows that tax preferences based on R&D expenditures can directly reduce the marginal cost of R&D activities, thus encouraging firms to perform more R&D activities (Bloom et al., 2002; Wilson, 2009). Other arguments claiming that tax incentives promote the R&D suggest that tax incentives also reduce business risk-taking (Gale & Brown, 2013) and influence resource allocation by transferring resources originally used for tax avoidance to R&D activities (Atanassov & Liu, 2019). Numerous studies have verified the stimulating effect of tax incentives across various countries (Bloom et al., 2002; Czarnitzki et al., 2011; Lokshin & Mohnen, 2012).

In addition to policy instruments, the selection process also deserves attention. Most studies treat government selection as a factor that brings bias to their regression and use the IV method or matching method to reduce this bias (Dimos & Pugh, 2016). It has not been widely realised that the selection process is also a factor that influences the R&D decisions of firms. Government screening leads to R&D competition among firms since they must stand out from other applicants before they can obtain fiscal support. As a result, firms may increase their R&D investments, cooperate more and perform R&D activities with higher returns (Chen et al., 2019).

The policy-based institutional environment is vital to innovation efficiency (Guan & Chen, 2012). Although the incentive policy instruments and selection process are shown to be effective in the practice of developed countries, they may lose efficiency in a developing context. Some studies have revealed incentive inefficiency in developing countries (Boeing, 2016; Chen et al., 2019), the causes of which are mostly ascribed to corruption and lack of transparency (Xu & Yano, 2017). The information asymmetry between the government and applicants and its impact on selective innovation policies based on 'picking the winners' have long been ignored.

The applicants for incentive programmes, as the executors of R&D projects, have an information advantage over the government, which allows them to send deceptive signals without being exposed (Davidson & Segerstrom, 1998; Li et al., 2019). For example, a deceptive signal can be sent by an increase in the quantity of innovation output at the expense of the quality of innovation (Hall & Harhoff, 2012). Adverse selection and moral hazard problems always arise under imperfect information. For selective policies, adverse selection occurs during the application period as firms embellish their innovation capability or achievement to meet the selection criteria, and moral hazard occurs in the execution period as firms deal with government inspections. Only a small body of literature has explored such deceptive behaviours in developing contexts. Li and Zheng (2016) verified a moral hazard in subsidy programmes in which firms may apply for a large number of minor patents to cater to the government. To our knowledge, Chen et al. (2019) is the only study on adverse selection; these authors found that firms may relabel administrative expenses as R&D investment when applying for HNTE status.

3. Data and indicators

3.1. Data

The data come from the annual survey by the Science and Technology Commission Shanghai Municipality (STCSM). STCSM sent questionnaires to technological enterprises in Shanghai every year since 2008[3],[4] The questions are mainly related to business performance, R&D activities and cooperation as well as other types of information. Since the investigation is not mandatory, approximately 10,000 questionnaires have been returned each year, which accounts for about 17% of the population. The survey thus provides unbalanced panel data from 2008 to 2016 with more than 101,000 observations. Figure 2(a) shows the number of observations in different districts of Shanghai and Figure 2 (b) describes the density of observations. A large number of samples are located in the central and eastern regions of Shanghai, which is consistent with the actual distribution of technological enterprises in Shanghai.

We omit illogical samples and winsorize variables at the 1% and 99% levels. After these procedures, 86,544 observations remain, among which large, medium-sized and small firms account for 4%, 11% and 84%, respectively.[5] Previous literature mostly focuses on listed firms or large and medium-sized firms, and small firms have long been neglected due to data availability. Our study fills this gap by using survey data that contain a large portion of small firms and are closer to the overall composition of the population.

3.2. Variable constructions

3.2.1. Dependent variable: innovation behaviour

This paper uses the number of patent applications in a particular year to reflect the innovation behaviour of firms. In China, there are three types of patents: invention patents, utility model patents and external design patents. According to Chinese patent law, invention patents refer to 'the technical solution for new products, new methods of production or its improvement', while the other two patent types are collectively called 'noninvention patents' or 'minor innovation' and refer to the design of or improvement in the shape, structure, combination or appearance of a product (Cheung & Lin, 2004; Xin et al., 2019). An invention patent must pass an examination for its utility, novelty, and non-obviousness before being granted, while noninvention patents are examined only in the utility dimension (Hu & Jefferson, 2009). Therefore, if firms are carrying out deceptive innovation, they may prefer to apply for noninvention patents.

Following Li and Zheng (2016), when the number of invention patent applications increases, substantive innovation is considered to have occurred. When the number of invention patent applications does not increase and the number of noninvention patent applications increases at the same time, deceptive innovation is considered to have occurred.

3.2.2. Independent variables

We use four dummy variables to measure the status of firms: preparing for the application of subsidy programmes/HNTE programme; receiving subsidy/being certified as HNTE. Since our data do not include a direct indicator of whether a firm is preparing to apply for a programme, a Propensity Score Matching (PSM) method is used to identify firms in the application period. This method shows that 7% and 8% of the firms are preparing for the subsidy programmes and HNTE programme, respectively. In the execution period, the proportions of subsidised firms and HNTEs are 13% and 26%, respectively.[6]

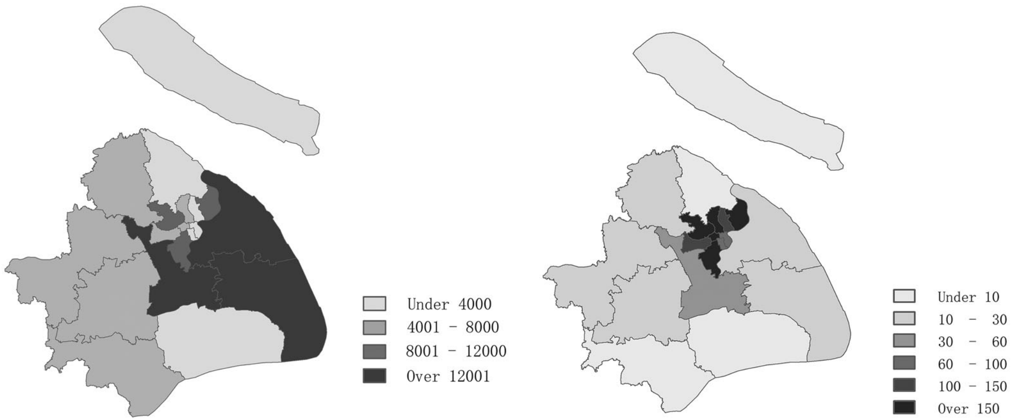

Figure 2. (a) Number of observations and (b) Density of observations.

3.2.3. Control variables

For controls, the innovation capabilities and R&D inputs of firms are vital factors that affect their R&D outputs. Following the theory of endogenous growth, we treat R&D activity as an innovation production process and consider innovation capability, R&D investment and R&D personnel as control variables. Cooperation is another factor that affects the innovation production process. For firms in developing countries, cooperation with foreign partners may bring new techniques and differential knowledge (Kafouros & Forsans, 2012). Thus, we use a dummy of whether a firm has a foreign partner as a control variable. We also take firm size and firm age into account since these factors may lead to different budget constraints, R&D experiences and attitudes toward new technologies (Huergo & Jaumandreu, 2004; Shefer & Frenkel, 2005).

All financial variables are initially deflated at the 2008 price level using the consumer price index (CPI) of Shanghai, and all variables except for the dummies are treated logarithmically. Table 1 provides the variable constructions and descriptive statistics.

4. Model specification

4.1. Firm innovation in the application period

The firm's innovation behaviour when it prepares to apply for the incentives can be specified as the following linear equations:

$$innovation_{it} = \beta_0 + \beta_1 prepare\_sub_{it} + \beta_2 X_{it} + \gamma_i + \varepsilon_{it} \tag{1}$$

$$innovation_{it} = \beta_0 + \beta_1 prepare\_hnte_{it} + \beta_2 X_{it} + \gamma_i + \varepsilon_{it} \, , \tag{2}$$

where the subscripts refer to firm i at year t; $innovation_{it}$ represents firm innovation, measured by the number of patent applications, invention patent applications and noninvention patent applications; $prepare\_sub_{it}$ and $prepare\_hnte_{it}$ are the main explanatory variables; and X_{it} is a vector of the aforementioned control variables. Their detailed

Table 1. Variable constructions and descriptive statistics.

Variable	Construction	Mean	St.d.
Dependent variables			
Patent	Number of patent applications / invention patent applications /	1.636	3.715
Invention patent	noninvention patent applications generated in the same year	0.665	1.877
Noninvention patent		0.971	2.662
Independent variables			
Prepare_sub	Dummy variable, takes the value of 1 if the firm is preparing to	0.070	0.255
Prepare_hnte	apply for the subsidy / HNTE programme	0.082	0.274
Incentive_sub	Dummy variable, takes the value of 1 if the firm received a	0.130	0.336
Incentive_hnte	subsidy / is a HNTE	0.264	0.441
Control variables			
Innovation capability	Total number of granted invention patent	1.355	4.755
R&D investment	R&D expenditure in this year (1,000 yuan)	2141.93	5348.18
R&D personnel	Number of R&D employees	17.576	32.825
Technical openness	Dummy variable, takes 1 if firm's main R&D partners are located overseas	0.038	0.191
Firm size	Total asset (1,000 yuan)	45312.59	126566.50
Firm age	Firm age	8.645	5.575
Observations		86,544	

Note: The variables Prepare_sub and *Prepare_hnte* are estimated by the authors; the detailed estimation method is provided in Section 4.1

construction is listed in Table 1. Furthermore, γ_i represents firm-fixed effects that capture any unobserved time-invariant firm heterogeneity, including industry, ownership and other features, and ε_{it} is the idiosyncratic error term.

$prepare\_sub_{it}$ and $prepare\_hnte_{it}$ are estimated by identifying potential applicants because we cannot readily observe whether a firm is preparing for an application. If a firm receives incentives in the next year, it can be considered to be preparing for the application in the current year,[7] i.e. $prepare_{i,t} = 1$ and $prepare_{i,t+1} = 0$. However, for those firms that never obtain a subsidy or certificate as an HNTE, there are two possibilities: they applied for the incentive but failed to be selected or did not apply. Therefore, their actual status needs to be identified.

Since there are various types of subsidies, firms may continue to apply for another programme after receiving one, which may distort the measurement results. We minimise this bias by using a subsample consisting of firms that receive subsidies only once and firms that never receive subsidies.

We use a yearly-layer propensity score matching (PSM) method for further identification. The treatment group consists of firms that are definitely in the preparing period (i.e. those receive incentives in the next year but not in this year), while the control group is composed of firms that are in an uncertain state (i.e. those do not receive incentives in this year or in the next year). Then, we match firms in the two groups year by year using a nearest-neighbor matching method with replacement.[8] The matched firms in the control group are considered to be in the application period.

Firms in the application period may have some common features that can be used as covariates in the matching. Both the highly innovative R&D projects needed for subsidy programme application and the rich innovation output needed for the HNTE status application require a high R&D input. Figure 3 shows the trend of average R&D intensity and average growth of R&D expenditure of firms before and after receiving incentives. We use R&D intensity and the growth rate of R&D expenditure as two main covariates in the matching. For other covariates, we also consider the innovation production process, i.e. the R&D expenditure and human resources (expenditure per R&D capita and the share of personnel with a bachelor's degree), and firm innovation capacity (granted innovation patents). We also control internationalisation (whether they have foreign suppliers, cooperators or markets) and incentive status (receiving another incentive or not).

4.2. Firm innovation in the execution period

The innovation behaviour of the firm after it has obtained the incentives can be specified by the following linear equations:

$$innovation_{it} = \beta_0 + \beta_1 incentive\_sub_{it} + \beta_2 X_{it} + \gamma_i + \varepsilon_{it} \tag{3}$$

$$innovation_{it} = \beta_0 + \beta_1 incentive\_hnte_{it} + \beta_2 X_{it} + \gamma_i + \varepsilon_{it}\ , \tag{4}$$

where $incentive\_sub_{it}$ and $incentive\_hnte_{it}$ are dummy variables indicating whether the firm has obtained a subsidy or has been certified as an HNTE, respectively. The meanings of the other variables remain unchanged.

To solve the problem of endogeneity, we employ the IV method. We construct instrumental variables from both industrial and spatial dimensions. Following Fisman and

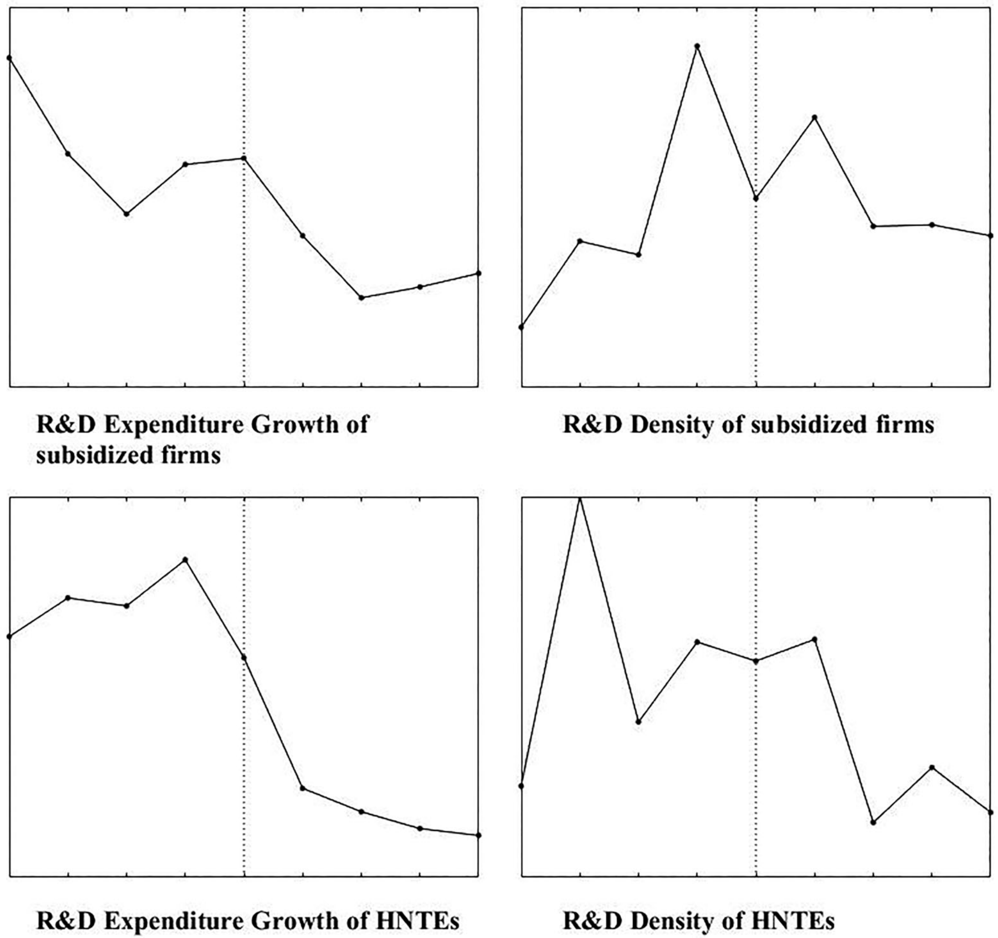

Figure 3. R&D inputs of subsidised firms and HNTE.

Svensson (2007), the industrial-dimension instrumental variable of firm i at year t is specified as the proportion of firms in the same industry that obtained incentives at year t-1. The share of firms that received incentives in the previous year is independent of the patent applications of individual firms. However, if a certain industry has a high ratio of firms that received incentives, it would be a key supporting industry in China's transition economy. Such industries are favoured by innovation policies, which means firms in these industries are more likely to receive incentives. Therefore, the instrument is correlated with the endogeneity variables and uncorrelated with our dependent variables.

The spatial-dimension instrumental variable is based on the different locations of firms. In Shanghai, the city is divided into 16 separate districts, and each district has a relatively independent district government, public financial system and growth plan, which allows us to capture the spatial difference of firms. We use educational resource abundance as the instrumental variable, which is measured by the student-teacher ratio of primary and secondary schools. Districts with higher educational resource abundance usually pay more attention to their future development and thus may invest more resources in supporting science, technology and education. In this case, firms in these districts may be provided with more R&D incentives. Moreover, due to the high labuor mobility and convenient transportation in Shanghai, the difference between primary and secondary schools may be less related to the labour resources available to firms. Therefore, educational resources in a district may be exogenous to a firm's innovation achievement.

5. Results

For the Hausman test, the fixed-effect model is recommended over the random-effect model. The empirical results are as follows.

5.1. Firm innovation in the application period

We first estimate $prepare\_sub_{it}$ and $prepare\_hnte_{it}$. Table 2 lists the bias between groups after matching. Most biases of the variables are under 5%, while the highest bias is 11.5%, which implies that the matched control group has no significant difference from the treatment group. Then, we regress Eq.(1) and Eq.(2). As shown in Table 3, the number of patent applications experiences a significant decline during the period when a firm is preparing for the application of subsidies. This may occur because the government pays more attention to whether the applicants are engaged in valuable R&D projects. Therefore, the innovation activities of firms in the application period focus on the

Table 2. Matching results

Variable	Subsidy Programmes (%bias)	HNTE Programme (%bias)
R&D intensity	2.2	−5.1
R&D Expenditure Growth	5.4	4.8
R&D Investment per capita	0.3	9.8
Human Resource	0.8	−3.1
Innovation capability	0.5	2.3
Openness	5.5	0.3
Current Incentive	2.6	11.5

Table 3. Firm innovation in the application period.

	Subsidy			HNTE Programme		
Variables	(1) Patents	(2) Invention Patents	(3) Noninvention Patents	(4) Patents	(5) Invention Patents	(6) Noninvention Patents
Prepare_sub	−0.0562***	−0.0214***	−0.0495***	–	–	–
	(−5.609)	(−2.722)	(−5.335)			
Prepare_hnte	–	–	–	0.0282***	0.00954	0.0246***
				(3.424)	(1.561)	(3.345)
Innovation capability	0.144***	0.153***	0.0218**	0.131***	0.138***	0.0229***
	(11.73)	(15.36)	(1.990)	(13.87)	(17.59)	(2.764)
R&D investment	0.0260***	0.0122***	0.0177***	0.0291***	0.0147***	0.0193***
	(13.27)	(8.910)	(10.53)	(14.80)	(10.40)	(11.47)
R&D personnel	0.0615***	0.0301***	0.0448***	0.0692***	0.0392***	0.0472***
	(12.42)	(9.066)	(10.11)	(13.92)	(11.11)	(10.84)
Firm size	0.0212***	0.0115***	0.0164***	0.0259***	0.0173***	0.0173***
	(5.809)	(4.306)	(5.167)	(6.767)	(5.844)	(5.298)
Technical openness	0.0789***	0.0547***	0.0390*	0.0660***	0.0481***	0.0342*
	(3.480)	(3.226)	(1.849)	(3.246)	(3.029)	(1.839)
Firm age	−0.0115***	−0.0110***	−0.00204	−0.0183***	−0.0156***	−0.00621***
	(−6.379)	(−7.016)	(−1.302)	(−10.64)	(−10.66)	(−4.196)
Constant term	0.0808**	0.0605**	0.00125	0.116***	0.0602**	0.0370
	(2.363)	(2.494)	(0.0410)	(3.311)	(2.268)	(1.216)
Observations	72,080	72,080	72,080	85,702	85,702	85,702
R^2	0.349	0.309	0.211	0.339	0.306	0.203

T-values in parentheses; ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

preliminary preparation of high-quality projects. It may be difficult to obtain full-fledged innovation outputs in this stage. Furthermore, the preparation of high-quality R&D projects usually requires a large amount of R&D resources. To meet such requirements, firms may suspend existing noncore R&D activities.

The number of patent applications increases when a firm is preparing for the application of the HNTE programme. However, in terms of the types of patents, the coefficient for Prepare_hnteit is positive and significant at the 1% level when using noninvention patent applications as the dependent variable, while the coefficient is nonsignificant when using invention patent applications as the dependent variable. This result implies that the increase in the number of patent applications is mainly due to noninvention patents and that some firms are engaged in deceptive innovation. The cash effective tax rate (ETR)[9] in China has a mean value of around 22% (Wang et al., 2018). This high tax rate makes firms highly motivated to obtain tax incentives and reduce their tax burden through HNTE certification. To stand out from other applicants, firms will inevitably engage in intensive R&D activities and develop more outputs. Since firms are required to report the number of R&D outputs instead of the details of R&D projects, deceptive innovation becomes a better choice.

5.2. Firm innovation in the execution period

Tables 4 and 5 report the results of Eq.(3) and Eq.(4), respectively, including the results both with and without controlling for endogeneity. The validity of our instruments is tested first. Both instruments pass the unrecognised test; the F-values of the first-stage regression are larger than 10 in both models, which rules out the existence of weak instruments; the *P*-values of Sargan test do not reject the null hypothesis of instrument exogeneity in all regressions; and the Hausman test suggests the IV method should be used. Therefore, the instruments are valid.

The subsidy, as listed in Table 4, significantly promotes the application for patents by 1.27%. The application for invention patents increased by 1.19%, which accounts for the vast majority of the increase in patent application. This confirms the conclusion of the application-period model: firms invest a large amount of resources in the preliminary preparation of high-quality projects at the early stage and carry out the project after receiving subsidies. In this way, firms can obtain considerable R&D outputs.

Surprisingly, although the tax instrument used for the HNTE programme is considered to encourage firm innovation, firms actually reduce their number of patent applications after they are identified as an HNTE. Tax deductions and other preferential policies decrease firms' motivation to perform R&D activities. This result is consistent with the conclusion of Brown et al. (2017), who found that an innovation incentive policy based on tax preferences usually promotes low-technology innovation, while policies that help firms obtain R&D financing are more effective. A possible explanation for this result may be related to the mechanism of the HNTE programme. Once a firm is certified as an HNTE, it will enjoy low corporate income taxes for three years and is not required to make additional R&D investment. This low tax rate greatly reduces the operating cost of HNTEs; thus, their motivation to obtain competitive advantage through R&D activities is weakened.

5.3. Summary and discussion

As shown in Table 6, we summarise the changes in the number of patent applications in different periods and under different incentives and calculate the net effect of the two

Table 4. Firm innovation in the execution period (Subsidy)

	FE			IV		
Variables	(1) Patents	(2) Invention patents	(3) Noninvention patents	(4) Patents	(5) Invention patents	(6) Noninvention patents
Incentive_sub	0.0869***	0.0756***	0.0421***	1.267***	1.191***	0.483
	(7.822)	(8.744)	(4.217)	(3.167)	(3.626)	(1.490)
Innovation capability	0.126***	0.133***	0.0220***	0.103***	0.109***	0.0174*
	(13.49)	(17.14)	(2.672)	(8.397)	(10.66)	(1.732)
R&D investment	0.0272***	0.0124***	0.0190***	0.00351	−0.00945*	0.0103*
	(13.99)	(9.045)	(11.41)	(0.517)	(−1.709)	(1.894)
R&D personnel	0.0677***	0.0382***	0.0462***	0.0321***	0.0102	0.0259***
	(13.66)	(10.89)	(10.63)	(2.794)	(1.109)	(2.806)
Firm size	0.0286***	0.0184***	0.0190***	0.0342***	0.0231***	0.0217***
	(7.493)	(6.326)	(5.811)	(4.899)	(3.980)	(4.085)
Technical openness	0.0671***	0.0495***	0.0339*	0.0400	0.0279	0.0241
	(3.311)	(3.131)	(1.829)	(1.246)	(1.036)	(0.948)
Firm age	−0.128***	−0.0967***	−0.0516***	0.0467	0.0595	0.0131
	(−11.42)	(−11.44)	(−5.242)	(0.720)	(1.116)	(0.250)
Constant term	0.205***	0.122***	0.0755**	−0.227	−0.267**	−0.0858
	(5.370)	(4.217)	(2.283)	(−1.499)	(−2.158)	(−0.717)
Observations	85,702	85,702	85,702	45,571	45,571	45,571
R^2	0.351	0.328	0.205	–	–	–
F-test of instruments	–	–	–	15.59	15.59	15.59
Sargan test	–	–	–	0.217	0.133	0.321

T-values in parentheses; ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Firm innovation in the execution period (HNTE programme).

	FE			IV		
Variables	(1) Patents	(2) Invention patents	(3) Noninvention patents	(4) Patents	(5) Invention patents	(6) Noninvention patents
Incentive_hnte	−0.0304*	−0.00919	−0.0262	−0.571**	−0.905***	0.0952
	(−1.712)	(−0.697)	(−1.644)	(−2.307)	(−4.560)	(0.419)
Innovation capability	0.128***	0.134***	0.0231***	0.114***	0.128***	0.0149
	(13.55)	(17.11)	(2.791)	(9.156)	(12.23)	(1.331)
R&D investment	0.0286***	0.0136***	0.0197***	0.0240***	0.0104***	0.0176***
	(14.69)	(9.890)	(11.85)	(9.190)	(5.028)	(8.101)
R&D personnel	0.0703***	0.0400***	0.0478***	0.0752***	0.0600***	0.0344***
	(14.10)	(11.31)	(10.98)	(8.285)	(8.307)	(4.277)
Firm size	0.0297***	0.0187***	0.0200***	0.0528***	0.0552***	0.0164
	(7.764)	(6.422)	(6.085)	(4.633)	(5.976)	(1.608)
Technical openness	0.0680***	0.0512***	0.0338*	0.0431	0.0147	0.0389
	(3.350)	(3.234)	(1.818)	(1.469)	(0.594)	(1.515)
Firm age	−0.127***	−0.0990***	−0.0489***	−0.0143	0.0894*	−0.0842
	(−11.29)	(−11.62)	(−4.989)	(−0.253)	(1.948)	(−1.630)
Constant term	0.201***	0.128***	0.0674**	−0.0768	−0.359***	0.170
	(5.320)	(4.441)	(2.070)	(−0.588)	(−3.373)	(1.466)
Observations	85,702	85,702	85,702	45,571	45,571	45,571
R^2	0.345	0.318	0.200	–	–	–
F-test of instruments	–	–	–	72.26	72.26	72.26
Sargan test	–	–	–	0.144	0.169	0.618

T-values in parentheses; ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

policies. The subsidy programmes, which focus on specific R&D projects and perform close supervision of firms, create a relatively transparent policy environment. Although the R&D outputs of firms experience a slight decrease in the application period, they increase soon after firms receive subsidies. The growth of patent applications mostly results from invention patents, which implies that substantive innovation is promoted. By contrast, the HNTE programme, which selects firms according to their previous R&D achievements and performs limited supervision, suffers from a relatively higher degree of imperfect information. We identify the adverse selection problem in the application period in which firms perform deceptive innovation by applying for a large number of noninvention patents to increase their patent stock. We also find a decline in patent applications in the execution period, which implies the existence of moral hazard. The net effect is calculated by the addition of coefficients in the two periods. Subsidies promote the application of invention patents, while the HNTE programme promotes the application of noninvention patents and suppresses the application of invention patents. The results imply that the 'picking-the-winners' incentive policies in China do

Table 6. Results summary and net effect.

	Subsidy programmes			HNTE programme		
Period	Patent application	Invention patent application	Noninvention patent application	Patent application	Invention patent application	Noninvention patent application
Application period	–	–	–	+	○	+
Execution period	+	+	○	–	–	○
Net effect	+	+	–	–	–	+

'+', '–' and '○' represent positive effect, negative effect and no significant effect, respectively.

not always successfully pick the winners and encourage firm innovation. The HNTE programme fails, at least in the short run, to derive substantive innovation.

Comparing the effects of the two incentive policies, we find the selection process is not always effective in selecting highly innovative firms since the information provided by firms may be misleading. The practice of subsidy programmes implies that properly established screening criteria and an appropriate validation mechanism can release imperfect information and may solve the adverse selection problem. In the execution period, the different performance between subsidised firms and HNTEs confirms the effectiveness of supervision in reducing moral hazard problems and guiding firms to engage in substantive innovation.

6. Robustness checks

6.1. Application period

Our strong settings for the application-period model may affect our empirical results. First, the length of the application period is set as one year in our previous regression; however, the period from the preliminary preparation of R&D projects to the formation of initial innovation results may be longer. Second, a nearest-neighbor matching method is used for the identification of firms in the application period; however, different matching methods may affect the results.

Table 7 presents the results of the robustness checks. We first extend this period to two years and then use kernel matching and radius matching for identification. The results show no significant differences compared with our previous regression.

Table 7. Firm innovation in the application period.

	Subsidy			HNTE Programme		
Variables	(1) Patents	(2) Invention Patents	(3) Noninvention Patents	(4) Patents	(5) Invention Patents	(6) Noninvention Patents
Robustness check: two-year application period						
Prepare_sub	−0.0568***	−0.0345***	−0.0407***			
	(−6.599)	(−5.299)	(−5.024)			
Prepare_hnte				0.0159**	0.00195	0.0167**
				(2.090)	(0.342)	(2.485)
Controls	yes	yes	yes	yes	yes	yes
Observations	72,080	72,080	72,080	85,702	85,702	85,702
R^2	0.349	0.309	0.210	0.340	0.306	0.204
Robustness check: Kernel matching						
Prepare_sub	−0.0738***	−0.0436***	−0.0515***			
	(−11.64)	(−9.186)	(−8.689)			
Prepare_hnte				0.00937	0.00140	0.0116**
				(1.477)	(0.293)	(2.079)
Controls	yes	yes	yes	yes	yes	yes
Observations	72,080	72,080	72,080	85,702	85,702	85,702
R^2	0.364	0.320	0.218	0.338	0.306	0.202
Robustness check: radius matching						
Prepare_sub	−0.0732***	−0.0434***	−0.0510***			
	(−11.54)	(−9.112)	(−8.609)			
Prepare_hnte				0.00899	0.00105	0.0113**
				(1.418)	(0.221)	(2.029)
Controls	yes	yes	yes	yes	yes	yes
Observations	72,080	72,080	72,080	85,702	85,702	85,702
R^2	0.364	0.320	0.218	0.338	0.306	0.202

T-values in parentheses; ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

6.2. Execution period

In this paper, selection bias has been controlled by using the IV method and adding control variables and individual fixed effect terms, but further testing is still needed. We provide a conditional difference-in-difference (CDID) regression as a robustness check.

For the standard DID model, the policy effect is estimated as follows:

$$\alpha_{DID} = \frac{1}{n^T}\sum_{i=1}^{n^T}(y_{i1}^T - y_{i0}^T) - \frac{1}{n^C}\sum_{j=1}^{n^C}(y_{j1}^C - y_{j0}^C),$$

where n^s is the number of observations in state s and y_{it}^s is the outcome variable of firm i in state s at time t. There are two states of firms in which T is the treatment group that receives R&D incentives and C is the control group that does not receive R&D incentives. Additionally, the time period t=0 denotes the period before firms receive incentives, and t=1 denotes the period in which the incentives take effect. The DID method is based on the premise that the treatment group and the control group are randomly assigned. To satisfy this parallel hypothesis, propensity score matching (PSM) can be used to pair samples from the two groups, and then a random environment can be artificially generated (Aerts & Schmidt, 2008). The CDID matching estimator is given by

$$\alpha_{CDID} = \frac{1}{n^T}\sum_{i=1}^{n^T}\left\{(y_{i1}^T - y_{i0}^T) - \sum_{j=1}^{n^C} W(i,j)(y_{j1}^C - y_{j0}^C)\right\},$$

where $W(i,j)$ is the weight between firm i in the treatment group and firm j in the control group, $\sum_{j=1}^{n^C} W(i,j) = 1$. The meanings of the other variables remain unchanged.

To estimate the effect of subsidies, we build a subsample of non-HNTEs to eliminate the influence of the HNTE programme. The treatment group consists of subsidised firms. We set the year they obtained subsidies as t=1 (after the policy) and the year before that as t=0 (before the policy). For the control group, we consider the last two consecutive years of unsubsidised firms, treating the first year as t=0 and the second year as t=1. Since the matching procedure ensures a parallel trend between the treated and untreated groups, the value of difference-in-difference can be seen as the net effect of subsidy programmes. We perform the same step for the unsubsidised subsample to estimate the effect of the HNTE programme. Considering that the programme affects the R&D process indirectly, its influence may take longer to be observed. Therefore, the second year after the firm was certified as an HNTE is set as t=1 (after the policy). Accordingly, the control group consists of samples that are observed for three consecutive years.

The matching is based on the core matching method with the same covariate as our main regression. We require the resulting matched sample to be within the common support interval and pass the balancing test. The results of the CDID analysis, as reported in Table 8, are similar to those of the IV method.

7. Summary

This paper explores the impact of selective R&D incentives on firm innovation. We develop the idea that the impact occurs before firms receive the incentive. The time is then divided into two periods: the period in which firms prepare themselves for

Table 8. Firm innovation in the execution period (CDID method).

	Before obtain subsidy (T=0)			After obtain subsidy (T=1)			Difference-in-difference
	Treatment group (1)	Control group (2)	Difference (3)=(1) − (2)	Treatment group (4)	Control group (5)	Difference (6)=(4) − (5)	(6) − (3)
Panel A: Subsidies							
Patents	1.490	1.159	0.331***	1.821	1.259	0.562***	0.232***
Invention patents	0.702	0.511	0.192***	0.877	0.539	0.337***	0.145**
Noninvention patents	0.786	0.649	0.137***	0.945	0.719	0.225***	0.088*
observations	1625	10603		1629	10603		
Panel B: HNTE programme							
Patents	3.864	1.580	2.284***	3.077	1.637	1.440***	−0.845***
Invention patents	2.639	0.662	1.977***	1.975	0.867	1.108***	−0.869***
Noninvention patents	1.225	0.918	0.307***	1.101	0.770	0.332***	0.025
observations	692	6307		692	6307		

***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

government screening (application period) and the period in which firms innovate with the incentive (execution period). We also consider this impact from an information asymmetry point of view. China's subsidy policy and High-and-New Technology Enterprise (HNTE) programme are used as representative policies of a higher degree and a lower degree of information symmetry, respectively. Our argument is based on unbalanced panel data on Shanghai technological enterprises from 2008 to 2016 and find that the selection process and the incentive process may lose efficiency in an imperfect information context. The IV method and CDID method are used to solve the problem of selection bias.

The empirical results suggest the existence of adverse selection of the HNTE programme. Firms may carry out deceptive innovation by increasing the number of patents at the expense of patent quality, thereby enhancing the possibility that they may obtain HNTE status. In the period when the incentives take effect, subsidy programmes successfully facilitate projects to form valuable outputs, while the HNTE programme fails to guide firms' innovation decision-making. The results also show that more detailed selection criteria and supervision can be helpful to gather information and eliminate the deviation of firms.

Notes

1. We do find some studies that examine the participation of R&D programmes, such as Blanes and Busom (2004) and Barajas and Huergo (2010), but these studies mostly focus on the factors that influence a firm's participation decisions, instead of the innovation behaviour after the firm has made such decisions.
2. In brackets are scores recommended by the central government of China since the local government in Shanghai does not disclose its specific scoring standard.
3. An enterprise registered in Shanghai with the status of a separate legal entity is called a 'technological enterprise' if it satisfies any three of the following conditions: (1) mainly engaged in innovation-related activities such as technology development, technology transfer, technology consulting, technology services, technology testing, or the invention and production of high-tech products (services); (2) proportion of R&D personnel not less than 5% of the total workforce; (3) the sum of technical income and sales income of high-tech products (services) accounts for not less than 30% of the total sales income; (4) annual R&D expenses

account for not less than 3% of total sales income; (5) has intellectual property rights such as patent, copyright, integrated circuit, new plant variety, or master proprietary technique.

4. Questionnaires were sent to more than 80,000 enterprises each year: approximately 30,000 firms located in Shanghai Zhangjiang high-tech parks (including 22 separate parks scattered in various parts of Shanghai); more than 50,000 firms located in different industrial parks and technical economic development areas; and firms located in other districts of Shanghai.
5. According to the Chinese government's standard of firm size, enterprises with fewer than 100 employees are defined as small firms, enterprises with more than 300 employees are defined as large firms, and enterprises between the two categories are medium-sized firms.
6. It is reasonable that the share of firms in the execution period is larger than the share in the application period. First, the government tends to choose previous winners (Boeing, 2016): 66.71% of subsidised firms received subsidies more than once, and 15.22% of subsidised firms received subsidies more than 5 times. The repeated receipt of subsidies increases the portion of subsidised firms but not the preparing firms. Second, a firm may maintain its HNTE status for up to 6 years, which increases the portion of HNTEs.
7. The HNTE status lasts three years. We treat only the year before the first year as preparing.
8. We provide the results using the kernel matching method and radius matching method as a robustness check.
9. The ETR represents the average rate of tax payments per unit of income or cash flow.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by The National Social Science Fund of China [Grant number 12&ZD026]; the Shanghai Soft Science Fund [Grant number 18692180500]; and the fund from Shanghai Academy of Social Science [Grant number 20140621].

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