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"SMES' INNOVATION POLICY" ON INNOVATION OF TECHNOLOGY-BASED SMES: A FUZZY REGRESSION DISCONTINUITY DESIGN*

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Abstract

We use the Fuzzy RD design to explore the influence of R&D subsidies and tax incentives in the "SMEs' Innovation Policy" on the innovation of technology-based SMEs. The results reveal that the "SMEs' Innovation Policy" can effectively stimulate the innovation of technology-based SMEs. Regardless of R&D subsidies or tax incentives means, the incentive effect of "SMEs' Innovation Policy" on strategic innovation is always stronger than substantial innovation. For the technology-based SMEs in the central-and-western region, the "SMEs' Innovation Policy" cannot significantly promote innovation, and may even inhibit it.

Keywords: SMEs' innovation policy, technology-based SMEs, substantive innovation, strategic innovation, fuzzy RDD
JEL Classification Codes: C21, D21, L53

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I. *Introduction*

Innovation of enterprises is an important foundation in promoting social and economic development. Since innovation has obvious externalities, which could reduce the enthusiasm of enterprises engaged in innovation, the government has to guide R&D activities of enterprises through policy means. From a worldwide perspective, many countries have been actively implementing innovation policies to stimulate and promote enterprise innovation. For example, the "Horizon 2020" implemented by the European Union aims to integrate the innovation resources of EU countries to improve the innovation efficiency of enterprises, the "2020 High-tech Strategy" implemented by the German Federal Government promotes innovation and development of high-tech enterprises by means of R&D subsidies, the strategic document "Our Growth Plan: Science and Innovation" released by UK in 2014 points out that government subsidies and tax incentives should be increased to encourage enterprises to innovate, and the "American Innovation Strategy" of the United States is devoted to subsidizing innovative enterprises through tax reduction and exemption, and promoting technological breakthroughs in high-tech fields. Since 2006, China has successively promulgated and implemented a series of innovation policies, such as "National Medium and Long-term Plan for Science and Technology Development (2006-2020)", "Outline of National Innovation-Driven Development Strategy", in order to play a leading role in innovation and encourage enterprises to innovate.

Enterprises are the main body of innovation, and technology-based small and medium-sized enterprises (henceforth, technology-based SMEs), as the key enterprises with the most innovative vitality and potential, are not only the indispensable force to promote China's development, but also the main supporter of China's technological innovation [e.g., Zhu et al. (2012)]. However, limited by enterprise size, enterprise scale and others, technology-based SMEs inevitably face some problems, for example, insufficient funds and poor financing channels for technological innovation. To effectively encourage technology-based SMEs to innovate, the government (Ministry of Science and Technology of China) has promulgated in 2015 the program "Opinions to promote the development of science and technology innovation of SMEs" (henceforth, "SMEs' Innovation Policy"), to actively support the innovative activities of technology-based SMEs and further enhance their innovation ability and promote their healthy development. The support of this policy for technology-based SMEs can be divided into two aspects: on the one hand, it provides R&D subsidies for innovative activities of technology-based SMEs; on the other hand, it encourages technology-based SMEs to actively participate in innovation by means of tax incentives. The questions worth thinking about are, in reality, how effective this policy is in encouraging innovation of technology-based SMEs? Can the incentive effect of this policy be further improved? How to improve it? Studying the above issues is not only conducive to understanding and revealing the mechanism of "SMEs' Innovation Policy", but also of great significance to the positioning design and perfect implementation of innovation policies under the innovation-driven development strategy in China.

This paper may have the following contributions. First, existing literatures show that there are many factors affecting enterprise innovation [e.g., Cornaggia et al. (2015), Hsu et al. (2014)]. However, there are few literatures focusing on the innovation of SME, in particular the causal relationship between government policy support and innovation of technology-based

SMEs. This paper enriches the research on the influencing factors of enterprise innovation. Second, there is the possible endogeneity between the policy target selection and the innovation outcomes of technology-based SMEs, which can lead to the lack of accuracy and credibility of the estimated results. In this paper, the quasi-natural experiment of SMEs identified as "technology-based SMEs" is used to investigate the impact of "SMEs' Innovation Policy" on enterprise innovation by means of Fuzzy Regression Discontinuity Design (henceforth, Fuzzy RRD) method. To a great extent, this alleviates the endogenous problems, thus making the research conclusions more reliable. Third, this paper empirically studies the influence of two different means (government subsidies and tax incentives) of "SMEs' Innovation Policy" on substantive and strategic innovation of enterprises, and further discusses the differences in policy effect on enterprise innovation in different regions. This not only provides empirical support for understanding the real impact of "SMEs' Innovation Policy" on enterprise innovation, but also provides policy reference for the government to further promote the policy of subsidy and tax reduction, reduce the tax burden of SMEs and stimulate the innovation vitality of SMEs.

The rest of the paper proceeds as follows. Section II describes the literature review. Section III discusses the model setting and the identification strategy. Section IV shows the data source and the variable description. Section V conducts the Fuzzy RDD analysis and discusses the empirical results. Section VI discusses the robustness of the estimation results. Finally, conclusions are drawn in section VII.

II. *Literature Review*

"Innovation failure" causes enterprises to face great risks and lack innovation motivation. Therefore, the government should participate in enterprise innovation and ensure the effective allocation of innovation resources by various policy means to promote enterprise innovation [e.g., Kang and Park (2012)]. The related studies can be sorted into five aspects: (1) "factors influencing enterprise innovation", (2) "R&D subsidies and enterprise innovation", (3) "tax incentives and enterprise innovation", (4) "innovation policies and technology-based SMEs" and (5) "policy evaluation and RDD method".

1. Factors Influencing Enterprise Innovation

The studies about factors influencing enterprise innovation can be summarized into four categories. The first one is the environmental factors. The market environment, the industry environment and the macro environment are mainly reflected in the impact of industry competition intensity and market distortion on enterprise innovation [e.g., Zhang et al. (2014), Dai and Liu (2015)]. The second one is the structural factors. The interaction between enterprises and external organizations, including the contact with suppliers, buyers and competitors, are mainly reflected in the influence of technological opportunities and knowledge spillovers on enterprise innovation [e.g., Granovetter (2005)]. The third one is the organizational factors. The organizational factors emphasizing the importance of the enterprise itself and internal factors, are mainly reflected in the impact of enterprise size, corporate culture and strategic management on enterprise innovation [e.g., Lin et al. (2010), Zhao and Wu (2015)].

The fourth one is the individual factors. They are mainly reflected in the influence of individual characteristics of entrepreneurs, senior executives and technical personnel on enterprise innovation [e.g., Zhang and Wu (2016)].

2. R&D Subsidies and Enterprise Innovation

There are different views on the impact of R&D subsidies on enterprise innovation. The first one is "incentive view", which believes that government subsidies can stimulate the innovation of enterprises [e.g., Zawalińska et al. (2018)], and this incentive effect is not only closely related to the scale of subsidy that enterprises receive, but also influenced by R&D spillover, embeddedness of R&D network and other factors [e.g., Buchmann and Kaiser (2018)]. The second one is "inhibition view", which considers that the rent-seeking behavior and the incentive distortion under the economic-oriented promotion assessment system will lead to excessive investment and unreasonable innovation structure [e.g., Wang et al. (2014)]. The third one is "irrelevance view", which considers that R&D subsidies may not have a significant "incentive" or "inhibition" effect on enterprise innovation due to the lax constraints of subsidies [e.g., Wu and Yang (2014)]. The fourth one is "non-linear view", which considers that there is an "inverted U-shaped" relationship between government R&D subsidies and enterprise innovation [e.g., Lin et al. (2015)].

3. Tax Incentives and Enterprise Innovation

There is no consensus on the relationship between tax incentives and enterprise innovation, which can be roughly divided into three categories: "incentive", "inhibition" and "moderate interval" . The majority of scholars hold the view of "incentive", and consider that tax incentives are beneficial to increase the quantity of new products and patent applications of enterprises [e.g., Kobayashi (2014), Crespi et al. (2016), Czarnitzki et al. (2011)]. Some scholars hold the view of "inhibition", and believe that tax incentives will crowd out enterprises' investment in R&D, thus inhibiting enterprise innovation [e.g., Tassey (2007), Lokshin and Mohnen (2012)]. A few scholars hold the view of "moderate interval" and believe that tax incentives are a conditional and differentiated incentive for enterprise innovation. This incentive effect has a threshold, and the policy intensity only within the optimal range can promote enterprise innovation [e.g., Zheng et al. (2020)].

4. Innovation Policies and Technology-based SMEs

Although there are debates about the effects of innovation policies on nurturing innovation of technology-based SMEs, the innovation policies are still widely implemented in many countries, in particular the developed countries [e.g., Howell (2017), Boeing (2016)]. The underlying mechanisms of innovation policies are alleviating the urgent financial constraints [e.g., Meuleman and De Maeseneire (2012)] and the potential risk of innovation [e.g., Manso (2011)] for technology-based SMEs. Among different kinds of policies, one of the most famous policy initiated by government of the PRC is "SMEs' Innovation Policy" initiated in 2015. This policy aims to support the innovation activities of technology-based SMEs by means of R&D subsidies and tax incentives. Until now, the deep understanding of the "SMEs' Innovation

Policy" is still limited, which is caused by the lack of accurate data of technology-based SMEs' and rigor methods of policy evaluation [e.g., Guo et al. (2016)].

5. Policy Evaluation and Regression Discontinuity Design

The RDD is widely used in applied work, and it becomes one of the most credible quasi-experimental research designs for identification, estimation and inference of treatment effects [e.g., Calonico et al. (2017)]. The RDD is first introduced by Thistlethwaite and Campbell (1960) as an important method for evaluating social programs. Their work generates a flurry of related activity, which subsequently dies out. Economists revive the approach [e.g., van der Klaauw (2002), Angrist and Lavy (1999)], formalize it [e.g., Hahn et al. (2001)], strengthen its estimation methods, and begin to apply it to many different research questions [e.g., Goldberger (2008)]. Over the last two decades, the RDD approach has been used to evaluate the impact of unionization [DiNardo and Lee (2004)], implementation public guarantees to SME [e.g., De Blasio et al. (2018)], limits on unemployment insurance [e.g., Black et al. (2007)], and delayed entry to kindergarten [e.g., McEwan and Shapiro (2008)] etc.

III. *Model Setting and Identification Strategy*

This paper uses Fuzzy RDD to investigates the actual effect of "SMEs' Innovation Policy" on the innovation of technology-based SMEs by means of R&D subsidies and tax incentives. We begin with the following equation:

$$Y_i = \omega + \lambda \cdot policy_i + \mu_i \tag{1}$$

where Y_i represents the innovation of SMI_i, including innovation output *patent*, substantive innovation *inn* and strategic innovation *noinn*; μ_i is a random disturbance term; *policy* is treatment variable, if the SMI_i is supported by "SMEs' Innovation Policy", $policy=1$, otherwise $policy=0$. The treatment variable *policy* has two different forms: R&D subsidy (*sub*) and tax incentive (*tax*).

Relevant government departments determine whether the target SME belongs to "technology-based SMEs" by taking the comprehensive score which is calculated based on the recently released "Evaluation Measures for Technology-based SMEs" (henceforth, "Evaluation Measures"). The "Evaluation Measures" clearly stipulates that SMEs are identified as "technology-based SMEs", which should meet the condition that the comprehensive score is not less than 60 points, and the calculation method for the comprehensive score of technology-based SMEs is shown in Table 1.

"SMEs' Innovation Policy" eligibility depends on the comprehensive score of SME. Using various SME characteristics such as scientific and technical personnel, and R&D investment, government can compute a comprehensive score, which is used to determining policy eligibility according to a discontinuous rule. The enterprises identified as "technology-based SMEs" could be supported by "SMEs' Innovation Policy", which may have an impact on the enterprise innovation.

Although "Evaluation Measures" is officially promulgated in 2017, it has already been

Table 1. Calculation Method for the Comprehensive Score

Evaluation index	Requirements	Score
Scientific and technical personnel (The proportion of scientific and technical personnel to the total number of employees in SMEs)	[30%,100%]	20
	[25%,30%)	16
	[20%,25%)	12
	[15%,20%)	8
	[10%,15%)	4
	[0,10%)	0
R&D investment (The proportion of total R&D expenses of enterprises to business income)	[30%,100%]	50
	[25%,30%)	40
	[20%,25%)	30
	[15%,20%)	20
	[10%,15%)	10
	[0,10%)	0
Scientific and technological achievement indicators (The type and number of intellectual property rights owned by the enterprise within the validity period)	One or more Type I patents	30
	Four or more Type II patents	24
	Three Type II patents	18
	Two Type II patents	12
	Only one Type II patent	6
	No patent	0

Note: Type I intellectual property rights refer to “Patent for Invention”, while Type II intellectual property rights refer to “Patent for Utility Model”, “Patent for Industrial Design” and software copyrights. The contents of the table are from the “Evaluation Measures for Technology-based SMEs” developed by the Ministry of Science and Technology, the Ministry of Finance and the State Administration of Taxation. (http://www.most.gov.cn/mostinfo/xinxifenlei/fgzc/gfxwj/gfxwj2017/201705/t20170510_132709.htm).

implemented before the formal promulgation, and there are only some slight differences in terms of execution strength in different regions. As the eligibility rules are not enforced perfectly before formal promulgation, some ineligible SMEs with score below the cutoff 60 are supported by “SMEs’ Innovation Policy” while some SMEs with score above the cutoff fail to enjoy the policy support. The combination of (1) “SMEs’ Innovation Policy” eligibility assigned discontinuously based on a score and a cutoff and (2) imperfect compliance with eligibility status, makes this study an example of Fuzzy RDD where the treatment status is only partially determined by the running variable (comprehensive score) and the predetermined cutoff 60.

To be concrete, the probability of SMEs being identified as “technology-based SMEs” is a discontinuous function of the comprehensive score:

$$P[policy_i=1\,|\,score_i]=\begin{cases} f_1(score_i), & \text{if } score_i\geq 60 \\ f_0(score_i), & \text{if } score_i<60 \end{cases} \tag{2}$$

where $score_i$ represents the comprehensive score of SME i. In the Fuzzy RDD, some of the SMEs with $score_i\geq 60$ fail to be identified as “technology-based SMEs” and some of the SMEs with $score_i<60$ can be recognized as “technology-based SMEs” despite being assigned to the control group. As a consequence, we use the binary variable D_i to denote whether the SME i is actually identified as “technology-based SMEs”. Our notation distinguishes between the treatment assigned $policy_i$ and the treatment actually received D_i. Using this notation, the defining feature of the Fuzzy RDD is that there are some SMEs for which $policy_i\neq D_i$.

By using Fuzzy RDD, we are typically interested in both the effect of being assigned to treatment (the effect of *policy*) and the effect of actually receiving treatment (the effect of *D*) on the outcome (innovation *Y*). Analytically, the estimation of the treatment effect in the Fuzzy RDD is often carried out by the two-stage least squares (2SLS) method. The following models illustrate how 2SLS analysis is carried out in this setting:

First-Stage Equation: $$policy_i=\alpha+\delta\cdot D_i+\beta\cdot k_1(score_i)+\gamma\cdot Z_i+\varepsilon_i \tag{3}$$

Second-Stage Equation: $$Y_i=\omega+\lambda\cdot policy_i+\theta\cdot k_2(score_i)+\varphi\cdot Z_i+\mu_i \tag{4}$$

where ε_i is the random error in the first stage regression and μ_i is the random error in the second stage regression. The first-stage equation in this model is estimated using ordinary least squares (OLS) regression. Then the predicted value of the mediator, $policy_i$, from the first-stage regression is used in place of $policy_i$ in the second-stage equation, and this equation is estimated using OLS, which in turn produces an estimate of λ. Standard errors in the second-stage regression are adjusted to account for uncertainty in the first stage. The function $k(score_i)$ represents the relationship between the running variable and the outcome. A variety of functional forms can be tested to determine which fits the data best, so that bias will be minimized, and the optimal polynomial order is judged by the Akaike Information Criterion (AIC). Similar to the Sharp RDD, in the Fuzzy RDD, extra steps need to be taken to ensure that the functional forms in both stage ($k_1(score_i)$ and $k_2(score_i)$) are correctly specified[1]. For the estimation in a Fuzzy RDD, the literature recommends that the same bandwidth can be used in both the first- and second-stage regressions [e.g., Imbens and Lemieux (2008)] for simplicity purposes[2]. Z_i represents the vector of control variables. Theoretically, there is no need to control other variables to achieve consistent regression estimation [e.g., Lee and Lemieux (2010)], however, adding control variables can eliminate sample selection bias and improve accuracy. Therefore, the characteristics of SMEs are controlled in the above equations.

IV. *Data Source and Variable Description*

1. Data Source

The enterprises of the A-share Small-and-Medium-Sized board are mostly SMEs with strong innovation ability; while the enterprises of Growth Enterprises Market (GEM) board, mainly have the huge development potential and innovation capacity. Since this paper focuses on the impact of "SMEs' Innovation Policy" on the innovation of technology-based SMEs, it is

[1] The parametric approach involves trying out polynomial functions of different orders and picking the model that fits the data the best. It is possible that the functional forms in the two regressions differ. However, in order to use the 2SLS method and use the 2SLS standard errors, the same functional form is often used for both regressions in practice.

[2] One can well imagine that the optimal bandwidth for the first-stage regression could be wider than the one for the second-stage regression, and using a wider bandwidth for first-stage regression might be desirable for efficiency reasons. However, if two different bandwidths are used for these two regressions, then the first-stage and second-stage regressions will be estimated based on different samples, which will greatly complicate the computation of standard errors for the estimates. Furthermore, it will greatly increase the number of potential sensitivity checks that one has to conduct with different bandwidth choices, since, instead of one, two bandwidths, as well as their combinations, have to be changed simultaneously.

reasonable to select listed enterprises of A-share Small-and-Medium-Sized board and GEM board as research samples. The listed enterprise data of China's A-share Small-and-Medium-Sized board and GEM board from 2010 to 2017 are mainly from CSMAR database and WIND database. The missing patent information of listed enterprises is manually collected and summarized after consulting the databases of the State Intellectual Property Office and the Chinese Academy of Sciences.

Considering the applicability of the Fuzzy RDD and the implementation time of "SMEs' Innovation Policy", the research "window" is set to the year 2015-2016. To be concrete, the research data selected starts from the year when the policy is implemented, and ends before the year when the "Evaluation Measures" is officially promulgated. During this period, the identification criteria for technology-based SMEs conform to the evaluation setting of Fuzzy RDD[3]. Therefore, we select the data from 2015 to 2016, and use Fuzzy RDD to investigate the impact of "SMEs' Innovation Policy" on the innovation of technology-based SMEs.

Furthermore, according to the "Statistical Measures for the Division of Large, Medium and Small Enterprises" released by the National Bureau of Statistics (see Appendix A), large enterprises that do not meet the criteria for SMEs are excluded from the data. For example, listed industrial enterprises with more than 1000 employees and operating income exceeding 4 billion are excluded, and listed enterprises in construction industry with operating income and total assets exceeding 8 billion are excluded, etc. Considering the integrity and validity of data, we delete the delisted enterprises, and eliminate the SMEs with obvious errors or too many missing values in key indicators. Finally, we obtain the final data which contains 1153 SMEs.

2. Variable Description

Since there is a certain time lag between R&D input and innovation output, the amount of R&D investment of SME cannot fully and timely reflect its actual innovation level. Therefore, this paper focuses on the "output" of innovation. The quantity of patent applications is chosen to measure the innovation output of SMEs for two reasons. First, the patent data is easy to obtain, and can be used as a stable and objective standard to effectively measure the innovation output of SMEs. Second, we choose the quantity of patent applications instead of the quantity of patent authorizations, because the patent authorization needs to go through a certain approval process, and this process will cause a certain time lag, which cannot timely reflect the innovation output of SMEs.

Furthermore, to clarify the influence of "SMEs' Innovation Policy" on the innovation, we follow the idea of Li and Zheng (2016) and distinguish the different innovation behaviors of SMEs. Specifically, the innovation behaviors of SMEs could be divided into two categories: substantive innovation and strategic innovation. The former is the core of enterprise innovation and the main driving force for enterprise development, which is measured by the quantity of "Patent for Invention" of SMEs (*inn*); the latter is the strategic behavior adopted by SMEs to

[3] The model design would be in line with the Sharp RDD after the promulgation of "Evaluation Measures". However, due to the permission of the database, the authors have not yet obtained the relevant data of A-share Small-and-Medium-Sized board enterprises and that of Growth Enterprises Market (GEM) board enterprises after the promulgation of "Evaluation Measures".

TABLE 2. VARIABLE DESCRIPTION

Type	Symbol	Description
Outcome variable	*patent*	Ln(quantity of patent applications +1)
	inn	Ln(quantity of "Patent for Invention" +1)
	noinn	Ln(quantity of "Patent for Utility Model" + quantity of "Industrial Design" +1)
Treatment variable	*sub*	Ln(amount of government subsidy)
	tax	Refund of taxes and fees received / (Refund of taxes and fees received + Tax payable)
Running variable	*score*	Score calculated according to "Evaluation Measures"
Control variable	*roa*	To measure the profitability of SMEs
	age	Ln(year of report - year of establishment of SME)
	state	Dummy variable, if state-owned SME 1, otherwise 0.

cater to the government, which is measured by the sum of the quantity of "Patent for Utility Model" and "Patent for Industrial Design" of SMEs, in other words, "Patent for Non-Invention" (*noinn*).

The government implements the "SMEs' Innovation Policy" for technology-based SMEs in two ways: R&D subsidies and tax incentives. Referring to existing relevant literature, the R&D subsidy amount shown in the annual report of the listed enterprise is used to measure the R&D subsidy (*sub*), and $\frac{\text{Refund of taxes and fees received}}{(\text{Refund of taxes and fees received} + \text{Tax payable})}$ is used to measure the tax incentive (*tax*).

Innovation is an activity that needs a lot of financial support, and SMEs with strong profitability often have more funds to carry out innovation activities. In addition, the age and the nature of enterprise often cause the deviation of policy bias, which will affect the innovation output of SMEs. To this end, we select the return on assets (*roa*), the enterprise age (*age*) and the state-owned SMEs (*state*) as the control variables, so as to more accurately identify the influence of "SMEs' Innovation Policy" on the innovation of technology-based SMEs. The specific description and definition of the selected variables are shown in Table 2.

Table 3 reports the descriptive statistic of data. The mean value of the comprehensive score is 68.836 and the minimum value is 0, indicating that both "technology-based SMEs" and "non-technology-based SMEs" exist in the research sample, and the majority of enterprises are eligible for "SMEs' Innovation Policy". The mean value of the quantity of patent applications is 60.203, and the mean value of non-invention patent applications quantity (sum of "Patent for Utility Model" and "Industrial Design") is 34.458, which is slightly higher than the mean value of invention patent applications ("Patent for Invention"). From the perspective of "SMEs' Innovation Policy", the amount of R&D subsidies received by SMEs varies greatly. The minimum value 0 indicates that there are SMEs that have not received R&D subsidies at all. The mean value of tax incentive is 0.283, with the minimum and maximum value of 0 and 1.234 respectively. In terms of return on assets, the minimum value is -0.286, which indicates that a few SMEs are unable to make profits. In addition, the mean value of age is 2.790, this indicates that the SMEs in the sample are generally not established for a long time. The mean value of state-owned SMEs is 0.098, indicating that most SMEs in the sample are non-state-

Table 3. Descriptive Statistics

Variables	Observation	Mean	Standard deviation	Min	Max
Comprehensive Score	1153	68.836	23.773	0	100
Quantity of patent applications	1153	60.203	154.153	0	2404
Quantity of "Patent for Invention"	1153	25.745	83.997	0	1995
Quantity of "Patent for non-Invention"	1153	34.458	94.729	0	1534
Quantity of "Patent for Utility Model"	1153	28.639	79.819	0	1354
Quantity of "Industrial Design"	1153	5.915	24.763	0	492
R&D subsidies	1153	2.841	7.663	0	1490940
Tax incentives	1153	0.283	0.291	0	1.234
Return on assets	1153	0.050	0.054	-0.286	0.361
Age	1153	2.790	0.273	1.791	4.111
SOE	1153	0.098	0.297	0	1

Note: From CSMAR database and WIND database.

owned, which is consistent with the reality.

V. *Fuzzy RDD Analysis*

1. Exploration

Graphical presentations provide a simple yet powerful way to visualize the identification strategy of the Fuzzy RDD. Therefore, before regression, the discontinuity caused by "SMEs' Innovation Policy" should be visually analyzed in order to check whether the outcome variables show systematic changes at the cutoff point.

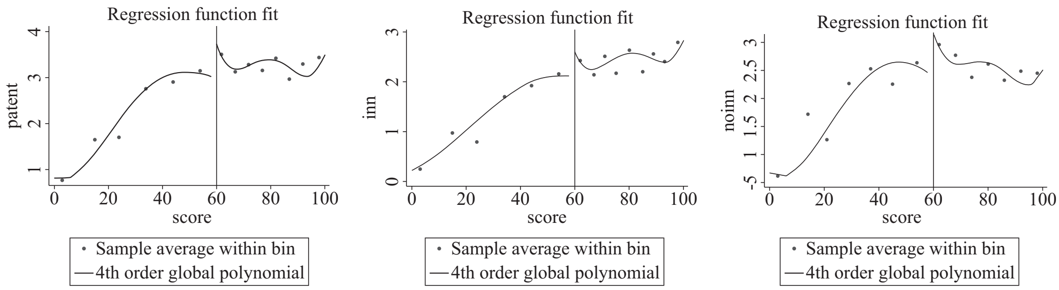
There are two different types of bins that can be used in the construction of Fuzzy RDD plots: bins that have equal length (evenly-spaced bins), and bins that contain the same number of observations but whose length may differ (quantile-spaced bins). Figure 1 shows the relationship between the outcome variables *patent*, *inn*, *noinn* and the running variable *score* by the evenly-spaced bins, and Figure 2 is the graphical presentation by quantile-spaced bins.

In the evenly-spaced bins case, since each bin has the same length, each bin has length equal to both the average and the median length on each side. Figure 1 shows that there is a sharp upward jump at the cutoff point in the relationship between outcomes and running variable.

Figure 2 presents the relationship between outcome and running variable in the quantile-spaced bins case. It is also shown that the innovation, the substantive innovation and the strategic innovation have obvious jump at the cutoff point, which indicates that "SMEs' Innovation Policy" has an impact on the innovation of technology-based SMEs.

To ensure the accuracy and effectiveness of RDD, it is necessary to visually inspect a graph of the density of the running variable (See Figure 3). If the RDD is valid (there is no manipulation around the cutoff point), then there should be no discontinuity observed in the number of observations just above or below the cutoff. Figure 3 depicts the distribution of the running variable, and *score* does not jump significantly at the cutoff point. Furthermore, McCrary (2008) offers a formal empirical test of this phenomenon that assesses whether the

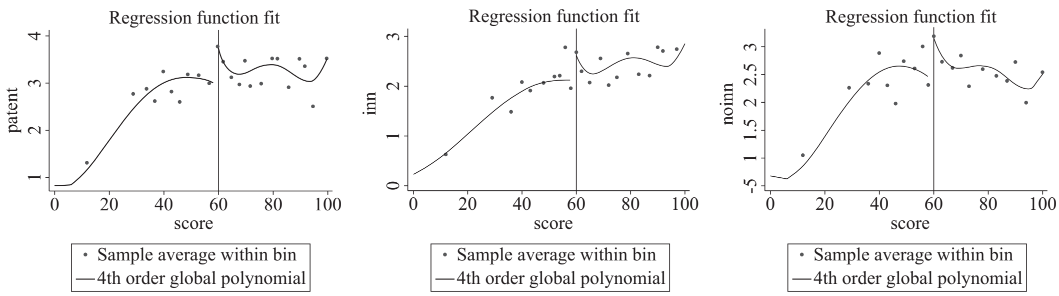
FIGURE 1. RELATIONSHIP BETWEEN SME INNOVATION AND COMPREHENSIVE SCORE IN THE EVENLY-SPACED BINS CASE



a. patent b. inn c. noinn

Note: Dots represent SMEs. The vertical line in the center of each graph designates a cutoff point, above which SMEs are assigned to the treatment and below which they are not assigned to the treatment.

FIGURE 2. RELATIONSHIP BETWEEN SME INNOVATION AND COMPREHENSIVE SCORE IN THE QUANTILE-SPACED BINS CASE



a. patent b. inn c. noinn

Note: Dots represent SMEs. The vertical line in the center of each graph designates a cutoff point, above which SMEs are assigned to the treatment and below which they are not assigned to the treatment.

discontinuity in the density of the running variable at the cutoff point. According the results of McCrary test, the density test statistic is 0.484 and t-value is 3.025, which indicates the distribution of running variables is continuous. In other words, the SMEs in the research sample cannot precisely control or manipulate the cutoff point and the comprehensive score, there is no significant difference in the distribution of SMEs on the left and right sides of the cutoff point.

Besides, Figure 4 depicts the relationship between the comprehensive score and R&D subsidies, while Figure 5 describes the relationship between the comprehensive score and tax incentives. It is shown that the "SMEs' Innovation Policy" gives strong support to technology-based SMEs ($score > 60$), and the SMEs on both sides of the cutoff point have great differences in R&D subsidies and tax incentives. This indirectly verifies the rationality of adopting the comprehensive score of SMEs as the running variable.

The graphs and prior discussion all focus on obtaining intent-to-treat estimates, in other words, the average impact for SMEs which are identified as "technology-based SMEs". We are

FIGURE 3. DISTRIBUTION OF COMPREHENSIVE SCORES

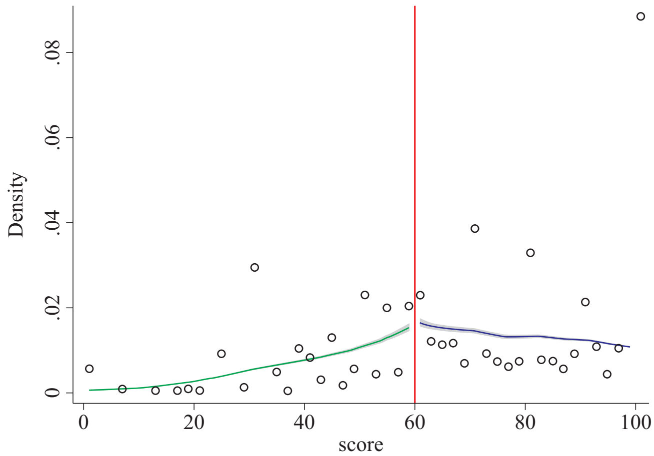


FIGURE 4. R&D SUBSIDIES AND COMPREHENSIVE SCORE

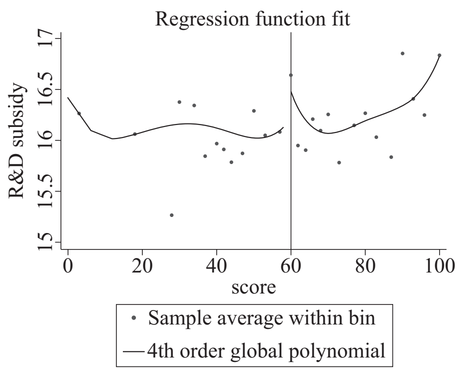
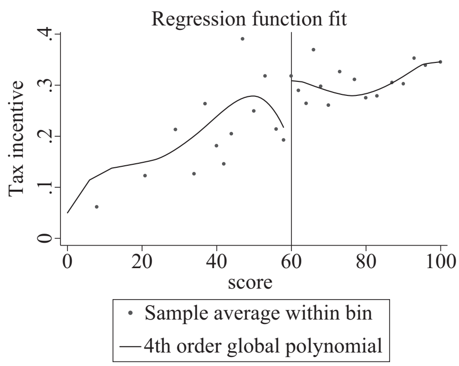


FIGURE 5. TAX INCENTIVES AND COMPREHENSIVE SCORE



also interested in obtaining unbiased estimates of the impact of the policy on technology-based SMEs which actually are supported by the R&D subsidy and/or tax incentive means of "SMEs' Innovation Policy".

2. R&D Subsidies of "SMEs' Innovation Policy" on the Innovation of Technology-Based SMEs

The research process is as follows: firstly, taking the innovation as the outcome variable, we investigate the influence of "SMEs' Innovation Policy" on the innovation of technology-based SMEs through R&D subsidies; secondly, taking *inn* and *noinn* as the outcome variables respectively, we discuss the influence of "SMEs' Innovation Policy" through R&D subsidies on the substantive innovation and the strategic innovation of technology-based SMEs, and

Table 4. First Stage Estimated Results for Technology-Based SMEs through R&D Subsidies

	sub	
D	0.558** (0.279)	0.578** (0.290)
roa	—	1.872 (2.003)
age	—	0.203 (0.292)
state	—	0.473 (0.311)
constant	18.884* (1.791)	-21.821* (11.580)
R^2	0.041	0.102
Obs	1162	1162

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

highlight their differences; thirdly, we divide the dataset into two subsamples (eastern region subsample & central-and-western region subsample), in order to explore whether the policy has different effects on the innovation of technology-based SMEs in different regions.

The bandwidth controls the width of the neighborhood around the cutoff. Choosing a smaller bandwidth will reduce the misspecification error (smoothing bias) of the local polynomial approximation, but will simultaneously tend to increase the variance of the estimated coefficients because fewer observations will be available for estimation. On the other hand, a larger bandwidth will result in more smoothing bias if the unknown function differs considerably from the polynomial model used for approximation, but will reduce the variance. Since there is a "bias-variance tradeoff", the choice of bandwidth is fundamental for the analysis and interpretation of Fuzzy RDD. The most popular approach in practice seeks to minimize the MSE of the local polynomial Fuzzy RDD estimator. Since the MSE of an estimator is the sum of its squared bias and its variance, this approach effectively chooses the bandwidth to optimize the "bias-variance tradeoff" . In this paper, we select the "Optimal Bandwidth" (henceforth, OB) by minimizing the MSE of the local polynomial Fuzzy RDD estimator (MSE-Optimal approach), and the bandwidth sensitivity is tested in the robustness checks section (section VI). The estimated results of "SMEs' Innovation Policy" on the innovation of technology-based SMEs through R&D subsidies are summarized in Table 4 and 5.

According to the estimation results in Table 4, no matter whether control variables are introduced, the identification as technology-based SMEs (*D*) has always a positive effect on their access to R&D subsidies, which indirectly confirms the effectiveness of the Fuzzy RDD. As shown in Table 5, R&D subsidies have incentive effect on the innovation of technology-based SMEs. Specifically, without control variables, the estimated coefficients for the R&D subsidies impact on innovation, substantive innovation and strategic innovation are 1.737, 1.180 and 1.680 respectively, and all of them are significant at the statistical level of 5% or 10%. After the introduction of control variables, the coefficient values decrease, but the influence direction of the policy does not change, and the goodness of fit (R^2) is improved on the whole. The abovementioned results show that the R&D subsidy of "SMEs' Innovation Policy" guides

Table 5. Second Stage Estimated Results for Technology-Based SMEs through R&D Subsidies

	patent		*inn*		*noinn*	
sub	1.737** (0.848)	1.549** (0.738)	1.180** (0.593)	1.055** (0.531)	1.680* (0.898)	1.537* (0.808)
roa	—	1.147 (3.290)	—	1.473 (2.365)	—	0.952 (3.602)
age	—	-0.063 (0.467)	—	0.022 (0.335)	—	-0.286 (0.511)
state	—	-1.189** (0.550)	—	-0.715* (0.395)	—	-1.087* (0.602)
constant	-24.831* (13.819)	-21.821* (11.580)	-16.357 (9.663)	-14.534* (8.323)	-24.764 (14.633)	-21.904* (12.078)
R^2	0.624	0.699	0.660	0.712	0.448	0.526
Obs	1162	1162	1162	1162	1162	1162

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

the innovation orientation of technology-based SMEs, and encourages technology-based SMEs to carry out substantive innovation activities. Besides, the R&D subsidy of "SMEs' Innovation Policy" can also promote the strategic innovation of technology-based SMEs. Compared with substantive innovation, the R&D subsidy has a more obvious incentive effect on strategic innovation.

3. Tax Incentives of "SMEs' Innovation Policy" on the Innovation of Technology-Based SMEs

This subsection explores the influence of tax incentives on the innovation of technology-based SMEs. The estimated results of the "first stage" and that of "second stage" are shown in Table 6 and Table 7 respectively.

The estimated results in Table 6 indicate that the tax incentives enjoyed by technology-based SMEs are higher than those of non-technology-based SMEs. The estimated results of the "second stage" (Table 7) show that the estimated coefficients of tax incentives on innovation, substantive innovation and strategic innovation are all significant at the significance level of 10%, which proves that the tax incentive of "SMEs' Innovation Policy" can significantly promote the innovation of technology-based SMEs. After introducing the control variables, the goodness of fit (R^2) is improved. Similar to the abovementioned effect of R&D subsidies, tax incentives have a positive effect on substantive innovation, however, technology-based SMEs prefer the strategic innovation to substantive innovation.

4. Different Regions

In this subsection, the research data are divided into the eastern region subsample and the central-and-western region subsample according to the location of the SMEs, in order that we can discuss whether "SMEs' Innovation Policy" has different impacts on the innovation of technology-based SMEs in different regions. The eastern region includes Beijing, Tianjin, Fujian, Guangdong, Guangxi, Hainan, Hebei, Jiangsu, Liaoning, Shandong, Shanghai and

TABLE 6. FIRST STAGE ESTIMATED RESULTS FOR TECHNOLOGY-BASED SMEs THROUGH TAX INCENTIVES

	tax	
D	0.152* (0.790)	0.159** (0.800)
roa	—	-0.824 (0.545)
age	—	-0.095 (0.080)
state	—	0.024 (0.087)
constant	0.962 (0.941)	1.193 (0.980)
R^2	0.051	0.083
Obs	1162	1162

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

TABLE 7. SECOND STAGE ESTIMATED RESULTS FOR TECHNOLOGY-BASED SMEs THROUGH TAX INCENTIVES

	patent		*inn*		*noinn*	
tax	8.680* (4.982)	8.280* (4.572)	7.038* (4.257)	6.838* (3.978)	7.809* (4.649)	7.640* (4.379)
roa	—	11.611* (6.328)	—	10.024* (5.406)	—	10.245* (6.061)
age	—	0.884 (0.816)	—	0.776 (0.710)	—	0.462 (0.782)
state	—	-0.373 (0.780)	—	-0.146 (0.678)	—	-0.304 (0.747)
constant	6.589 (6.068)	5.109 (5.772)	6.649 (5.185)	5.417 (5.022)	4.875 (5.663)	4.412 (5.529)
R^2	0.392	0.459	0.189	0.252	0.306	0.349
Obs	1162	1162	1162	1162	1162	1162

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

Zhejiang, while other provinces belong to the central-and-western region. The estimation results of the first stage in the Fuzzy RDD are shown in Table 8.

For SMEs located in the eastern region, being identified as technology-based SMEs can get more R&D subsidies and greater tax incentives. However, in the central-and-western region, "being a technology-based SME" does not have a significant impact on R&D subsidies and tax incentives. The estimated results of the second stage are summarized in Table 9.

According to the estimated results shown in Table 9, the R&D subsidy of "SMEs' Innovation Policy" has an obvious incentive effect on the innovation of technology-based SMEs in the eastern region, and compared with the substantive innovation, the strategic innovation can be influenced more strongly by the R&D subsidy. However, in the central-and-western region, the incentive effect of R&D subsidies is not obvious, and R&D subsidies may even inhibit the innovation of technology-based SMEs. Similarly, the tax incentive of "SMEs' Innovation Policy" has also an obvious incentive effect on the innovation of technology-based

TABLE 8. FIRST STAGE ESTIMATED RESULTS GROUPED BY REGIONS

	sub				*tax*			
	Eastern region subsample		Central-and-western region subsample		Eastern region subsample		Central-and-western region subsample	
D	0.648*** (0.250)	0.667** (0.250)	-0.481 (0.431)	-0.443 (0.428)	3.179** (1.520)	3.594** (1.541)	1.004* (0.540)	6.438 (9.237)
roa	—	3.683*** (1.400)	—	3.691 (2.350)	—	-14.984 (9.921)	—	7.163 (9.562)
age	—	0.116 (0.235)	—	-0.612 (0.424)	—	-1.229 (1.549)	—	0.599 (1.196)
state	—	0.421 (0.270)	—	0.362 (0.308)	—	2.018 (1.772)	—	-0.235 (0.905)
constant	17.744*** (0.856)	17.377*** (1.107)	15.625 (0.835)	17.346 (1.490)	25.409 (17.625)	30.704 (18.592)	23.494 (21.492)	1.328 (4.447)
R^2	0.053	0.123	0.010	0.051	0.036	0.070	0.045	0.086
Obs	895	895	243	243	895	895	243	243

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

TABLE 9. SECOND STAGE ESTIMATED RESULTS GROUPED BY REGIONS

	Outcome variables	R&D subsidies		Tax incentives	
		sub	R^2	*tax*	R^2
Eastern region	*patent*	1.082** (0.456)	0.824	6.217* (3.654)	0.604
	inn	1.591** (0.347)	0.810	4.684 (3.047)	0.493
	noinn	1.047** (0.501)	0.721	5.237 (3.394)	0.555
Central-and-western region	*patent*	-0.292 (1.034)	0.808	6.101 (10.917)	0.660
	inn	0.331 (0.791)	0.817	4.645 (9.556)	0.506
	noinn	-0.868 (1.432)	0.467	9.261 (14.172)	0.234
(with control variables)					
Eastern region	*patent*	0.970** (0.417)	0.845	5.536* (2.992)	0.681
	inn	0.530* (0.313)	0.819	4.179* (2.541)	0.576
	noinn	0.946** (0.465)	0.748	4.812* (2.896)	0.610
Central-and-western region	*patent*	-0.373 (1.163)	0.820	6.438 (9.237)	0.665
	inn	0.253 (0.852)	0.821	5.511 (8.404)	0.550
	noinn	-0.986 (1.632)	0.514	8.982 (11.524)	0.282

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

SMEs in eastern region, and the impact of tax incentives for strategic innovation is stronger than that for substantive innovation.

Generally, in the eastern region, "SMEs' Innovation Policy" can stimulate both the substantive innovation and the strategic innovation of technology-based SMEs. Compared with the policy impact on substantive innovation, this policy is more beneficial to encourage technology-based SMEs to engage in strategic innovation. In the central-and-western region, the technology, human resources and economic foundation are relatively weak, which makes "SMEs' Innovation Policy" difficult to effectively stimulate the innovation of technology-based SMEs, in particular the substantive innovation.

VI. *Robustness Checks*

To verify the validity of the previous estimates and prove that the regression results do not depend on the special settings of the model, we will conduct the following robustness tests: (1) continuity-based test for control variables, (2) test of sensitivity to bandwidth choice, (3) nonparametric test, (4) placebo cutoffs test, (5) extreme value test, (6) parametric test with different functional forms. Limited by the length of the article, the results of robustness test below are based on the full sample, and the robustness test results based on the regional subsamples are shown in the Appendix B.

1. Continuity-Based Test for Control Variables

The fundamental idea behind this falsification test is that, since the predetermined control variables could not have been affected by the treatment (*sub* and *tax*), the null hypothesis of no treatment effect should not be rejected if the Fuzzy RDD is valid. A statistical analysis is required in order to reach a formal conclusion, and the analysis is implemented by choosing a different optimal bandwidth for each control variable analyzed. Taking the control variable *roa* as an example, the point estimate is very close to zero (-0.001) and the robust p-value is 0.817, so we find no evidence that, at the cutoff, treated and control SMEs differ systematically in this control variable. In other words, there is no evidence that the *roa* is discontinuous at the cutoff. To provide a complete falsification test, the same estimation and inference procedure should be repeated for all control variables. The continuity-based test results for control variables are shown in Table 10.

According to the test results, all point estimates are small and all 95% robust confidence intervals contain zero, with p-values ranging from 0.158 to 0.817. In other words, there is no empirical evidence that these predetermined variables are discontinuous at the cutoff.

2. Test of Sensitivity to Bandwidth Choice

Since there is a "bias-variance tradeoff", the choice of bandwidth is fundamental for the analysis and interpretation of Fuzzy RDD. Table 11 reports the estimated results by using MSE-Optimal approach. OB represents optimal bandwidth, "OB+1" means adding 1 to the optimal bandwidth and "OB+2" means adding 2 to the optimal bandwidth, and so on. The test results show that the coefficients are significant at the statistical level of 5% or 10%, and the

Table 10. Results of Continuity-Based Test for Control Variables

Control variable	MSE-Optimal Bandwidth	Fuzzy RDD Estimator	Robust Inference		Eff. Number Observations
			P-value	95% Conf. Interval	
roa	13.312	-0.001	0.817	[-0.022, 0.013]	440
age	17.288	0.027	0.158	[-0.011, 0.071]	505
state	15.910	-0.035	0.606	[-0.165, 0.096]	461

Table 11. Test Results of Sensitivity to Bandwidth Choice

Outcome variables	Bandwidth choice	Estimator	
		sub	*tax*
patent	OB-2	1.617** (0.790)	6.188* (3.524)
	OB-1	1.970** (0.928)	6.022* (3.546)
	OB	1.737** (0.848)	8.680* (4.982)
	OB+1	1.649* (0.923)	6.241* (3.516)
	OB+2	1.793* (1.048)	5.702* (3.263)
inn	OB-2	1.191** (0.606)	4.796* (2.796)
	OB-1	1.599** (0.638)	4.796* (2.776)
	OB	1.180** (0.593)	7.038* (4.257)
	OB+1	1.694*** (0.594)	5.885** (2.660)
	OB+2	1.269* (0.752)	5.512** (2.737)
noinn	OB-2	1.571* (0.829)	5.871* (3.396)
	OB-1	1.761* (1.032)	5.983* (3.523)
	OB	1.680* (0.898)	7.809* (4.649)
	OB+1	1.740* (1.036)	5.933* (3.563)
	OB+2	1.746* (1.021)	5.402* (3.162)

Note: OB represents Optimal Bandwidth; ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

bandwidth change has no significant impact on the regression results. The estimation results of Fuzzy RDD are robust.

3. Nonparametric Test

The parametric approach tries to pick the right model to fit a given dataset, while the

Table 12. Nonparametric Estimation Results

Kernel function type	Treatment variable	Outcome variable	Estimator	Treatment variable	Outcome variable	Estimator
Trigonometric kernel function	*sub*	*patent*	1.980** (0.917)	*tax*	*patent*	5.944* (3.369)
		inn	1.659*** (0.600)		*inn*	5.885** (2.667)
		noinn	1.806* (1.757)		*noinn*	5.645* (3.256)
Uniform kernel function	*sub*	*patent*	2.202** (1.015)	*tax*	*patent*	8.579*** (3.241)
		inn	1.884*** (0.613)		*inn*	7.169** (3.888)
		noinn	2.105* (1.181)		*noinn*	8.228** (3.361)
Epanechnikov kernel function	*sub*	*patent*	2.107** (0.993)	*tax*	*patent*	5.824* (3.159)
		inn	1.791*** (0.616)		*inn*	5.795** (2.674)
		noinn	1.901* (1.129)		*noinn*	5.985* (3.236)

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

nonparametric approach tries to pick the right dataset to fit a given model. Parametric Fuzzy RDD depends on the specific form of the function, which may lead to the wrong setting of the model. Therefore, this subsection uses three different kernel functions for nonparametric estimation. The test results are reported in Table 12, and it is shown that the use of nonparametric approach (trigonometric, uniform and epanechnikov) for estimation will not cause obvious changes in the regression results, which further proves that the estimation results are reliable. In fact, the estimation with parametric approach has many advantages, in particular for implementing Fuzzy RDD. Instead of taking nonparametric estimation as a substitute for parametric estimation, it is better to regard it as a supplement to parametric estimation.

4. Placebo Cutoffs Test

This falsification test replaces the true cutoff value by another value at which the treatment status does not really change, and performs estimation and inference using this fake or placebo cutoff point. The expectation is that no significant treatment effect will occur at placebo cutoff values.

We conduct statistical estimation and inference for Fuzzy RDD treatment effects at artificial cutoff points, using local-polynomial methods within an optimally-chosen bandwidth around the fake cutoff to estimate treatment effects on the outcome. We set the fake cutoff point at 50,58,59,61,62 and 70 respectively, if the estimated results of Fuzzy RDD are also significant at these artificial cutoff points, the results of Fuzzy RDD are not credible. The results of placebo cutoffs test are shown in Table 13.

In Table 13, the true cutoff of 60 is included in order to have a benchmark to compare. All other cutoffs are artificial or placebo, in the sense that treatment did not actually change at those points. We find that in all artificial cutoff points, the p-values are above 0.1. Therefore,

TABLE 13. RESULTS OF PLACEBO CUTOFFS TEST

Treatment variable	Outcome variable	Alternative cutoff	MSE-Optinal bandwidth	Fuzzy RDD Estimator	Robust Inference		Eff. Number Observations
					Robust p-value	95% Conf. Interval	
sub	patent	50	18.163	1.939	0.355	[-1.290, 3.597]	421
		58	12.186	-0.236	0.473	[-0.884, 0.410]	423
		59	17.372	0.330	0.309	[-0.420, 1.715]	248
		60	17.338	1.737***	0.002	[0.361, 1.688]	364
		61	14.217	-0.237	0.399	[-0.902, 0.359]	457
		62	13.452	-0.326	0.252	[-0.884, 0.232]	444
		70	7.286	-191.100	0.946	[-499.959, 535.466]	209
	inn	50	18.712	1.344	0.421	[-1.129, 3.065]	421
		58	18.764	0.720	0.913	[-9.838, 11.279]	552
		59	8.989	1.106	0.112	[-0.164, 2.278]	244
		60	9.271	1.180**	0.018	[0.130, 1.391]	364
		61	14.503	0.753	0.160	[-0.297, 1.804]	452
		62	13.777	0.752	0.154	[-0.281, 1.785]	439
		70	7.545	-150.730	0.971	[-1240.61, 1287.22]	209
	noinn	50	17.263	3.086	0.370	[-2.036, 6.737]	405
		58	11.978	0.002	0.993	[-0.627, 0.633]	326
		59	10.635	0.416	0.191	[-0.627, 3.061]	313
		60	10.438	1.680*	0.094	[-0.297, 3.819]	402
		61	14.519	0.268	0.619	[-0.788, 1.324]	452
		62	13.668	0.395	0.431	[-0.587, 1.377]	439
		70	7.289	-204.800	0.947	[-1103.71, 667.083]	209
tax	patent	50	18.242	-1.931	0.461	[-15.281, 6.922]	426
		58	12.186	5.098	0.669	[-18.293, 28.489]	423
		59	8.757	7.121	0.113	[-1.706, 16.145]	248
		60	8.928	8.680*	0.076	[-0.611, 12.194]	364
		61	14.217	-1.087	0.753	[-7.869, 5.995]	457
		62	13.452	-2.191	0.820	[-21.054, 16.672]	444
		70	7.322	-6.062	0.847	[-66.246, 54.406]	209
	inn	50	18.711	-2.179	0.619	[-11.542, 6.874]	426
		58	18.399	4.848	0.474	[-8.431, 18.128]	531
		59	9.204	5.807	0.154	[-2.178, 13.792]	317
		60	9.271	7.038*	0.098	[-0.105, 10.342]	364
		61	14.748	-1.683	0.726	[-11.099, 7.731]	457
		62	13.870	-2.715	0.813	[-25.166, 19.736]	444
		70	7.518	-7.024	0.715	[-43.366, 29.731]	209
	noinn	50	17.544	-2.307	0.582	[-21.884, 12.284]	410
		58	11.436	3.362	0.699	[-13.660, 20.385]	330
		59	10.777	7.267	0.210	[-4.105, 18.639]	317
		60	10.300	7.809*	0.085	[-0.7724, 15.078]	406
		61	14.860	-5.930	0.788	[-49.119, 37.258]	457
		62	14.095	-1.364	0.820	[-13.120, 10.391]	471
		70	7.358	-6.394	0.719	[-78.948, 54.435]	209

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%.

we conclude that the outcomes of interest do not jump discontinuously at the artificial cutoffs considered.

TABLE 14. RESULTS OF EXTREME VALUE TEST

Treatment variable	Outcome variable	Estimator	Treatment variable	Outcome variable	Estimator
	patent	1.453* (0.783)		*patent*	5.320* (3.124)
sub	*inn*	1.567* (0.917)	*tax*	*inn*	4.899* (2.672)
	noinn	1.436* (0.791)		*noinn*	5.183* (3.147)

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

TABLE 15. PARAMETRIC ANALYSIS WITH DIFFERENT FUNCTIONAL FORMS

	patent		*inn*		*noinn*	
	Treatment estimate	p-value	Treatment estimate	p-value	Treatment estimate	p-value
R&D subsidy						
Treatment effect	**1.737****		**1.180****		**1.680***	
Model 1	1.786**	0.049	1.234**	0.041	1.760*	0.094
Model 2	1.824**	0.047	1.006**	0.049	1.789*	0.090
Model 3	1.803**	0.022	1.267**	0.037	1.807*	0.093
Tax incentive						
Treatment effect	**8.680***		**7.038***		**7.809***	
Model 1	7.791*	0.076	7.329*	0.081	7.653*	0.085
Model 2	8.265*	0.092	7.195*	0.087	7.019*	0.096
Model 3	8.215*	0.086	7.463*	0.081	7.659*	0.086

Note: Model 1 is "simple linear", Model 2 is quadratic, Model 3 is cubic; ***, ** and * respectively mean significant at the level of 1%, 5% and 10%.

5. Extreme Value Test

The sample can be limited to a comprehensive score of [20,80], and a total of 761 SMEs are selected. These SMEs account for about 65% of the total samples. The Fuzzy RDD is conducted for this sample without extreme values, and the results are shown in Table 14.

According to results shown in Table 14, the coefficients of "SMEs' Innovation Policy" on innovation, substantive innovation and strategic innovation of technology-based SMEs have some changes[4] compared with the full sample, but the differences are not obvious. The results are not affected by the extreme values, which confirms the reliability of the Fuzzy RDD estimation in this paper.

6. Parametric Test with Different Functional Forms

We select the appropriated functional form for the regression estimation, starting from a simple linear regression and adding higher-order polynomials ("simple linear", "quadratic" and

[4] As the sample size decreases, the variance increases and the significance decreases.

"cubic") to it. The estimated results are shown in Table 15. It is found that changing the functional form of $k(\text{score}_i)$ does not significantly affect the estimation results of the Fuzzy RDD.

VII. *Conclusion and Policy Suggestions*

The popularity of the Fuzzy RDD has grown markedly over the last decades, and it is now used frequently in economics, political science, and many other disciplines. The Fuzzy RDD method has the great advantages in policy evaluation and causal inference, and we choose this method to discuss the impact of "SMEs' Innovation Policy" on innovation of technology-based SMEs for the following reason: even if the SMEs can influence the running variable (comprehensive score) that determines the treatment effect of "SMEs' Innovation Policy", as long as the influence is not enough to enable the SMEs to accurately manipulate the score, the policy treatment effect at the cutoff point will still present a random experiment.

This paper uses the Fuzzy RDD to explore the influence of R&D subsidies and tax incentives in the "SMEs' Innovation Policy" on the innovation of technology-based SMEs. The empirical results show that the "SMEs' Innovation Policy" can effectively stimulate the innovation of technology-based SMEs, and both R&D subsidies and tax incentives can promote the innovation. Furthermore, regardless of R&D subsidies or tax incentives, the incentive effect of "SMEs' Innovation Policy" on strategic innovation is always stronger than substantial innovation. In addition, for the technology-based SMEs in the eastern region, the "SMEs' Innovation Policy" has a significant incentive effect, while for those in the central-and-western region, the "SMEs' Innovation Policy" cannot significantly promote innovation, and may even inhibit it.

Based on the research conclusions of this paper, the following suggestions are put forward:

Firstly, "SMEs' Innovation Policy" guides the innovation direction of technology-based SMEs and stimulates the enthusiasm of technology-based SMEs to carry out substantive innovation activities. Nevertheless, compared with substantive innovation, the incentive effect of policy on strategic innovation is more obvious. Therefore, relevant government departments should improve the "admittance" for SMEs to enjoy "SMEs' Innovation Policy", and avoid using too much government resources for SMEs engaged in strategic innovation. On the other hand, relevant government departments should help SMEs, especially technology-based SMEs, to enhance their motivation of substantive innovation, for example, by means of "Funding for invention patent application", and let technology-based SMEs pay attention to the balance between the innovation quantity and the innovation quality.

Secondly, the implementation effect of "SMEs' Innovation Policy" is obviously different in different regions. In the central-and-western region, the R&D subsidy of "SMEs' Innovation Policy" may even inhibit the innovation of technology-based SMEs. Therefore, relevant government departments should further improve the supervision and control of subsidy funds to achieve "precise support" for technology-based SMEs located in the central-and-western region.

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Appendix

Appendix A: Statistical Measures for the Division of Large, Medium and Small Enterprises

Table A. Statistical Classification of Large, Medium, Small and Micro Enterprises

Industry name	Indicator name	Measuring unit	Large	Medium	Small	Micro
Agriculture, forestry, animal husbandry and fishery	Business income(Y)	ten thousand yuan	Y≥20000	500≤Y<20000	50≤Y<500	Y<50
Industry	Employee(X)	person	X≥1000	300≤X<1000	20≤X<300	X<20
	Business income(Y)	ten thousand yuan	Y≥40000	2000≤Y<40000	300≤Y<2000	Y<300
Construction industry	Business income(Y)	ten thousand yuan	Y≥80000	6000≤Y<80000	300≤Y<6000	Y<300
	Total assets(Z)	ten thousand yuan	Z≥80000	5000≤Z<80000	300≤Z<5000	Z<300
Wholesale industry	Employee(X)	person	X≥200	20≤X<200	5≤X<20	X<5
	Business income(Y)	ten thousand yuan	Y≥40000	5000≤Y<40000	1000≤Y<5000	Y<1000
Retail industry	Employee(X)	person	X≥300	50≤X<300	10≤X<50	X<10
	Business income(Y)	ten thousand yuan	Y≥20000	500≤Y<20000	100≤Y<500	Y<100
Transportation industry	Employee(X)	person	X≥1000	300≤X<1000	20≤X<300	X<20
	Business income(Y)	ten thousand yuan	Y≥30000	3000≤Y<30000	200≤Y<3000	Y<200
Warehouse industry	Employee(X)	person	X≥200	100≤X<200	20≤X<100	X<20
	Business income(Y)	ten thousand yuan	Y≥30000	1000≤Y<30000	100≤Y<1000	Y<100
Postal industry	Employee(X)	person	X≥1000	300≤X<1000	20≤X<300	X<20
	Business income(Y)	ten thousand yuan	Y≥30000	2000≤Y<30000	100≤Y<2000	Y<100
Accommodation industry	Employee(X)	person	X≥300	100≤X<300	10≤X<100	X<10
	Business income(Y)	ten thousand yuan	Y≥10000	2000≤Y<10000	100≤Y<2000	Y<100
Catering	Employee(X)	person	X≥300	100≤X<300	10≤X<100	X<10
	Business income(Y)	ten thousand yuan	Y≥10000	2000≤Y<10000	100≤Y<2000	Y<100
Information transmission industry	Employee(X)	person	X≥2000	100≤X<2000	10≤X<100	X<10
	Business income(Y)	ten thousand yuan	Y≥100000	1000≤Y<100000	100≤Y<1000	Y<100
Software and information technology services	Employee(X)	person	X≥300	100≤X<300	10≤X<100	X<10
	Business income(Y)	ten thousand yuan	Y≥10000	1000≤Y<10000	50≤Y<1000	Y<50
Real estate development and management	Business income(Y)	ten thousand yuan	Y≥200000	1000≤Y<200000	100≤Y<1000	Y<100
	Total assets(Z)	ten thousand yuan	Z≥10000	5000≤Z<10000	2000≤Z<5000	Z<2000
Property management	Employee(X)	person	X≥1000	300≤X<1000	100≤X<300	X<100
	Business income(Y)	ten thousand yuan	Y≥5000	1000≤Y<5000	500≤Y<1000	Y<500
Leasing and business services	Employee(X)	person	X≥300	100≤X<300	10≤X<100	X<10
	Total assets(Z)	ten thousand yuan	Z≥120000	8000≤Z<120000	100≤Z<8000	Z<100
Other unlisted industries	Employee(X)	person	X≥300	100≤X<300	10≤X<100	X<10

Appendix B: Robustness Checks by Regions

Table B1. Results of Continuity-Based Test for Control Variables (Eastern Region)

Control variable	MSE-Optimal Bandwidth	Fuzzy RDD Estimator	Robust Inference		Eff. Number Observations
			P-value	95% Conf. Interval	
roa	10.785	0.001	0.875	[-0.017, 0.021]	338
age	19.953	0.087	0.103	[-0.017, 0.192]	426
state	16.671	-0.077	0.203	[-0.229, 0.048]	409

Table B2. Results of Continuity-Based Test for Control Variables (Central-and-Western Region)

Control variable	MSE-Optimal Bandwidth	Fuzzy RDD Estimator	Robust Inference		Eff. Number Observations
			P-value	95% Conf. Interval	
roa	11.261	-0.003	0.826	[-0.033, 0.026]	71
age	12.715	0.015	0.903	[-0.231, 0.261]	76
state	10.533	0.086	0.509	[-0.170, 0.344]	71

Table B3. Test Results of Sensitivity to Bandwidth Choice (Eastern Region)

Outcome variables	Bandwidth choice	Estimator *sub*	Estimator *tax*
patent	OB-2	2.049**	4.668*
		(0.968)	(2.738)
	OB-1	2.112**	4.757*
		(0.871)	(2.876)
	OB	1.082**	6.217*
		(0.456)	(3.654)
	OB+1	1.968**	6.783*
		(0.817)	(3.516)
	OB+2	1.830**	6.705*
		(0.814)	(3.749)
inn	OB-2	1.449**	3.437
		(0.642)	(2.752)
	OB-1	1.476**	3.458
		(0.581)	(2.791)
	OB	1.591**	4.684
		(0.347)	(3.047)
	OB+1	1.336**	3.909
		(0.545)	(2.586)
	OB+2	1.169*	3.322
		(0.544)	(2.677)
noinn	OB-2	1.906*	3.588
		(0.994)	(3.630)
	OB-1	1.952**	4.480
		(0.910)	(3.784)
	OB	1.047**	5.237
		(0.501)	(3.394)
	OB+1	1.870**	4.449
		(0.858)	(3.531)
	OB+2	1.777**	4.385
		(0.853)	(3.643)

Note: OB represents Optimal Bandwidth; ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

Table B4. Test Results of Sensitivity to Bandwidth Choice (Central-and-Western Region)

Outcome variables	Bandwidth choice	Estimator *sub*	Estimator *tax*
patent	OB-2	-0.659	5.382
		(1.824)	(16.265)
	OB-1	-0.354	4.255
		(0.928)	(10.818)
	OB	-0.292	6.101
		(1.034)	(10.917)
	OB+1	0.763	2.788
		(1.923)	(5.508)
	OB+2	-0.275	6.843
		(1.448)	(17.57)
inn	OB-2	0.232	4.468
		(0.445)	(13.409)
	OB-1	0.137	3.421
		(0.439)	(8.638)
	OB	0.331	4.645
		(0.791)	(9.556)
	OB+1	0.176	2.222
		(0.431)	(4.401)
	OB+2	0.173	1.493
		(0.271)	(2.268)
noinn	OB-2	0.564	6.148
		(1.015)	(18.542)
	OB-1	0.919	4.994
		(2.280)	(12.658)
	OB	-0.868	9.261
		(1.432)	(14.172)
	OB+1	-0.365	3.415
		(5.151)	(6.677)
	OB+2	-0.375	2.331
		(5.868)	(3.343)

Note: OB represents Optimal Bandwidth; ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

Table B5. Nonparametric Estimation Results (Eastern Region)

Kernel function type	Treatment variable	Outcome variable	Estimator	Treatment variable	Outcome variable	Estimator
Trigonometric kernel function	*sub*	*patent*	12.012** (0.834)	*tax*	*patent*	4.443* (2.075)
		inn	1.380** (0.557)		*inn*	3.783* (1.656)
		noinn	1.894*** (0.874)		*noinn*	4.354* (2.168)
Uniform kernel function	*sub*	*patent*	1.785** (0.809)	*tax*	*patent*	5.951* (3.264)
		inn	1.143** (0.533)		*inn*	4.100* (2.318)
		noinn	1.784** (0.871)		*noinn*	5.846* (3.213)
Epanechnikov kernel function	*sub*	*patent*	2.082** (0.831)	*tax*	*patent*	4.526* (2.167)
		inn	1.403** (0.549)		*inn*	3.941* (2.158)
		noinn	1.962** (0.882)		*noinn*	4.300 (3.625)

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

Table B6. Nonparametric Estimation Results (Central-and-Western Region)

Kernel function type	Treatment variable	Outcome variable	Estimator	Treatment variable	Outcome variable	Estimator
Trigonometric kernel function	*sub*	*patent*	12.962 (76.527)	*tax*	*patent*	32.558 (69.947)
		inn	8.440 (48.788)		*inn*	26.027 (55.766)
		noinn	16.744 (101.630)		*noinn*	39.197 (83.666)
Uniform kernel function	*sub*	*patent*	-2.265 (7.630)	*tax*	*patent*	10.372 (16.989)
		inn	-1.114 (5.219)		*inn*	8.216 (15.002)
		noinn	-3.822 (10.648)		*noinn*	15.013 (21.655)
Epanechnikov kernel function	*sub*	*patent*	-16.365 (159.730)	*tax*	*patent*	24.456 (47.487)
		inn	-9.490 (95.730)		*inn*	18.525 (36.329)
		noinn	-22.438 (213.930)		*noinn*	30.834 (59.121)

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

Table B7. Results of Placebo Cutoffs Test (Eastern Region)

Outcome variable	Alternative cutoff	Treatment variable *sub*		Treatment variable *tax*	
		MSE-Optinal bandwidth	Fuzzy RDD Estimator	MSE-Optinal bandwidth	Fuzzy RDD Estimator
patent	58	10.310	-0.551 (2.384)	12.305	2.026 (12.904)
	59	21.616	1.326 (0.963)	20.509	6.472 (7.483)
	60	13.455	1.082** (0.456)	13.784	6.217* (3.654)
	61	18.780	-0.444 (0.286)	18.809	0.014 (0.814)
	62	16.003	0.302 (0.477)	16.047	-9.802 (43.565)
inn	58	8.389	2.095 (3.891)	11.318	-0.041 (0.090)
	59	16.080	0.517 (0.824)	16.820	3.253 (3.350)
	60	14.033	1.591** (0.347)	12.907	4.684 (3.047)
	61	18.473	0.506 (0.519)	18.336	0.015 (0.062)
	62	12.554	-0.709 (1.134)	15.936	0.017 (0.065)
noinn	58	10.308	-0.678 (2.542)	14.957	-0.036 (0.078)
	59	16.028	1.095 (0.721)	16.390	0.105 (0.065)
	60	14.825	1.047** (0.501)	15.429	5.237 (3.394)
	61	14.787	0.065 (0.670)	15.435	0.021 (0.066)
	62	12.040	0.275 (0.453)	16.463	-3.771 (25.244)

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%.

Table B8. Results of Placebo Cutoffs Test (Central-and-Western Region)

Outcome variable	Alternative cutoff	Treatment variable *sub*		Treatment variable *tax*	
		MSE-Optinal bandwidth	Fuzzy RDD Estimator	MSE-Optinal bandwidth	Fuzzy RDD Estimator
patent	58	7.775	-0.456 (1.461)	13.310	5.288 (12.772)
	59	8.797	0.571 (0.487)	16.070	5.834 (3.879)
	60	11.024	-0.292 (1.034)	15.344	6.101 (10.917)
	61	9.731	0.995 (0.711)	12.190	-13.409 (35.168)
	62	12.359	4.453 (6.757)	10.078	-29.476 (91.106)
inn	58	8.204	2.094 (2.319)	12.745	-13.068 (13.382)
	59	9.358	3.660 (4.571)	15.831	0.028 (0.065)
	60	10.598	0.331 (0.791)	10.780	4.645 (9.556)
	61	10.372	1.751 (1.224)	10.743	-28.149 (100.850)
	62	12.359	4.453 (6.757)	9.374	0.033 (0.106)
noinn	58	8.765	0.734 (1.250)	12.201	-7.291 (12.083)
	59	10.209	16.961 (69.802)	15.506	0.027 (0.065)
	60	10.024	-0.868 (1.432)	11.484	9.261 (14.172)
	61	9.260	1.037 (0.767)	11.014	-22.356 (75.537)
	62	10.170	4.890 (6.029)	9.831	-39.764 (119.120)

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%.

Table B9. Results of Extreme Value Test (Eastern Region)

Treatment variable	Outcome variable	Estimator	Treatment variable	Outcome variable	Estimator
	patent	1.996* (1.050)		*patent*	5.474* (3.193)
sub	*inn*	1.429** (0.590)	*tax*	*inn*	4.201* (2.319)
	noinn	1.934* (1.059)		*noinn*	4.396* (2.461)

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().

Table B10. Results of Extreme Value Test (Central-and-Western Region)

Treatment variable	Outcome variable	Estimator	Treatment variable	Outcome variable	Estimator
	patent	5.653 (12.069)		*patent*	8.795 (11.260)
sub	*inn*	3.158 (5.039)	*tax*	*inn*	5.720 (9.640)
	noinn	5.431 (9.370)		*noinn*	12.712 (18.199)

Note: ***, ** and * respectively mean significant at the level of 1%, 5% and 10%; robust standard error is shown in brackets ().