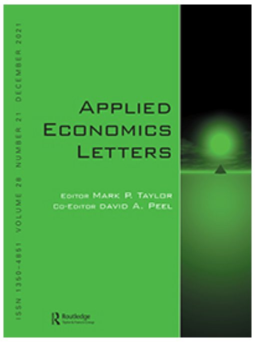

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Selective R&D subsidies and firms' application strategies

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ABSTRACT
'Picking-the-winners' selective R&D subsidies are provided to a few firms with high innovation capabilities. Thus, the applicants for subsidies might send misleading signals to stand out from others. This paper explores firms' application strategies and finds that firms tend to increase the quantity of their R&D outputs as a signal of being highly innovative, even at the expense of reducing innovation quality.

KEYWORDS
Selective R&D subsidy; application strategy; major innovation; minor innovation

JEL CLASSIFICATION
L53; O31; O38

I. Introduction

'Picking-the-winners' selective R&D subsidies are widely used in developing countries to help a few innovative firms develop new technologies and catch up with their counterparts in developed countries (Howell 2017). However, imperfect information and thus the principal-agent problem between the government and firms make it difficult to achieve the effective allocation of public R&D resources.

In the literature on R&D subsidy allocation, most studies focus on the 'principal' side, i.e. how the government selects qualified applicants (Boeing, 2016), while 'agent' behaviour has long been ignored. In fact, firms might send misleading signals to camouflage their innovation ability, which prevents the government from distinguishing imposters from truly innovative firms. Related studies are based mostly on theoretical models (Aguirre and Beitia 2017; Li, Su, and Lai 2019), and the first empirical evidence was provided by Zhao et al. (2018), who find that firms may relabel their management expenses as R&D investments as a signal of frequent R&D activities. The existence of fraudulent firms weakens the treatment effect of subsidies (Dai and Wang 2019). There is still room for improvement in the empirical literature. First, in addition to reporting inflated R&D investments, firms might also send signals by expanding previous R&D achievements; this possibility should be further explored. Second, it is necessary to verify whether these signals affect government decisions.

This paper contributes to the principal-agent literature by providing new evidence on the application strategies of firms. We focus on a typical selective R&D subsidy program with explicit screening criteria: the High-and-New Technology Enterprise (HNTE) program in China. Applicants to the HNTE program must satisfy the following R&D input criteria: (1) R&D personnel account for over 10% of total employment and (2) R&D intensity exceeds a threshold (which varies with firm size); as well as the following R&D output criteria: (3) technological income accounts for over 60% of income and (4) ownership of intellectual property (Dai and Wang 2019). Once these criteria are met, applicants are scored and receive a 10% tax credit if their scores exceed 70.

We first consider the determinants of HNTEs using a probit model, which helps us judge whether the government can identify highly innovative applicants. Then, we explore firms' application strategies in terms of both the quantity and quality

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dimensions of their R&D outputs. In particular, we use a two-step selection model to correct for potential self-selection bias.

II. Data

We use firm-year data on Shanghai technological enterprises provided by the Science and Technology Commission Shanghai Municipality (STCSM) of China. Since the screening criteria for the HNTE policy were implemented in 2008, we use a sample for 2008–2018, with 114,003 observations. To exclude the potential bias induced by the R&D input threshold, we also construct a subsample of 80,153 observations that satisfy the input criteria described in the introduction[1], including 33,176 HNTEs and 46,686 non-HNTEs.

III. Empirical specification

The number of patents is a good way to measure R&D output. There are three kinds of patents in China: invention patents, utility model patents and external design patents. The last two patents are called noninvention patents, require several months to be granted, and are approved at a rate of 70%. In contrast, the inspection of invention patents is stricter and takes more than two years, and only 30% of the applications are granted.[2] Invention patents embody greater novelty and effort. Therefore, we classify firms' R&D outputs into major innovations (invention patents) and minor innovations (noninvention patents) following Cheung and Lin (2004). Imposters may tend to patent more minor innovations as a signal since noninvention patents require less R&D effort and have shorter grant lags and higher approval rates than invention patents.

The following probit model describes the determinants of HNTEs:

$$\begin{aligned}\mathrm{HNTE}^{*}_{\mathrm{it}} &= \alpha_0 + \alpha_1\mathrm{Outputs}_{\mathrm{it}} + \alpha_2\mathrm{personnel}_{\mathrm{it}}\\ &+ \alpha_3\mathrm{intensity}_{\mathrm{it}} + \alpha_4\mathrm{subhist}_{\mathrm{it}} + \alpha_5\mathrm{SOE}_{\mathrm{it}} + \alpha_6\mathrm{size}_{\mathrm{it}}\\ &+ \alpha_7\mathrm{age}_{\mathrm{it}} + \delta_{\mathrm{t}} + \varepsilon_{\mathrm{it}},\\ \mathrm{HNTE}_{\mathrm{it}} &= \begin{cases} 1, & \textit{if } \mathrm{HNTE}^{*}_{\mathrm{it}} \geq 0,\\ 0, & \textit{otherwise},\end{cases}\end{aligned} \tag{1}$$

where $\mathrm{HNTE}_{\mathrm{it}}$ is a dummy variable for whether firm *I* is an HNTE in year *t*. The first three explanatory variables relate to HNTE criteria (1), (2) and (4). $\mathrm{Outputs}_{\mathrm{it}}$ is the number of patents granted in year *t*, and we also consider *innovation quality* measured by the share of invention patents. $\mathrm{personnel}_{\mathrm{it}}$ denotes the share of R&D personnel, and $\mathrm{intensity}_{\mathrm{it}}$ denotes R&D intensity. Other controls include $\mathrm{subhist}_{\mathrm{it}}$ (a dummy variable for subsidy history), $\mathrm{SOE}_{\mathrm{it}}$ (a dummy variable for state-owned enterprises), $\mathrm{size}_{\mathrm{it}}$ (firm size measured by total assets) and $\mathrm{age}_{\mathrm{it}}$ (firm age). δ_{t} is the year fixed effect, and $\varepsilon_{\mathrm{it}}$ is the normally distributed error term.

We further consider firms' application strategies. Following Shaver (1998), we employ a two-step selection model to correct for potential self-selection bias. The first step is to estimate the application choice model:

$$HNTE_{it} = \begin{cases} 1, ifHNTE^{*}_{it} \leq 0\\ 0, otherwise\end{cases} \tag{2}$$

where *$apply_{it}$ is a dummy variable for whether firm* *I* is preparing an application for the HNTE program in year *t*. It is estimated through propensity score matching following Luo and Sun (2020), where the observations that become an HNTE in the subsequent year constitute the treatment group and other observations constitute the control group. The matched observations are considered to be applicants for the HNTE program.[3] $\mathrm{Selection}_{\mathrm{it}}$ is a vector of measurable firm attributes including all the variables we use in propensity score matching and all the control variables in Eq.3. $\in_{it}$ is the error term. The second step is to add a correction factor to the performance model:

[1]Criterion (3) is not included in the analysis due to data limitations.
[2]Source: http://www.cnipa.gov.cn/
[3]For details, see Luo and Sun (2020). We use nearest-neighbour matching to pair the observations. The covariates used in matching include the growth rate of R&D expenses, R&D intensity, R&D expenses per capita, the share of R&D personnel, firm innovation capacity and R&D funds from other programs.

$$\text{Outputs}_{\text{it}} = \beta_0 + \beta_A \text{apply}_{\text{it}} + \beta' \text{Controls}_{\text{it}} + \beta_\lambda \lambda_{\text{it}} + \text{ind}_i + \omega_t + \mu_{\text{it}},$$
$$\text{where}\lambda = \begin{cases} \phi\,(\gamma\prime s)/\Phi(\gamma\prime s)\text{if apply}_{\text{it}} = 1, \\ -\phi(\gamma\prime s)/[1-\Phi(\gamma\prime s)]\text{if apply}_{\text{it}} = 0 \end{cases}. \quad (3)$$

where $\text{Outputs}_{\text{it}}$ and apply_{it} are mentioned above. $\text{Controls}_{\text{it}}$ include $\text{expense}_{\text{it}}$ (R&D expenses),$\text{rdemployee}_{\text{it}}$ (the number of employees engaged in R&D activity), $\text{capacity}_{\text{it}}$ (innovation capacity measured by invention patent stock), size_{it} and age_{it}. $\phi(\cdot)$ and $\Phi(\cdot)$ are the probability density function and cumulative distribution function, respectively, of the standard normal distribution.[4] Other variables remain unchanged. We also consider industrial and time heterogeneity. μ_{it} is the error term.

IV. Results

Table 1 presents the results from estimating Eq.1. The results show that HNTEs usually have more R&D outputs than other technological enterprises. However, if we consider the different types of R&D outputs, HNTEs are characterized by more minor innovation outputs and lower innovation quality. These findings support our assumption that the government may not accurately assess the true value of R&D outputs and identify firms that are effective in developing major innovations. The results also show that the input criteria are merely a threshold condition. Once firms meet the criteria, the inputs of R&D personnel no longer increase firms' likelihood of being selected. Thus, the quantity-based application strategy might be more cost-effective for firms than improving their innovation quality.

Next, we estimate the selection model (Table 2). To rule out the effect of the HNTE program itself, we drop the observations after firms become HNTEs. Compared with nonapplicant firms, applicants to the HNTE program produced more minor innovation outputs, while their major innovation outputs did not increase. Their innovation quality is also lower than that of nonapplicants. For robustness, we also regress Eq.3 as a fixed effects model, and the results lead to the same conclusion.[5]

Table 1. Determinants of HNTEs.

	Full-sample			Subsample		
Variables	1	2	3	4	5	6
Innovation outputs	0.00634***			0.00331**		
	(0.00221)			(0.00148)		
Major		0.00313			0.000443	
		(0.00505)			(0.00301)	
Minor		0.00758***			0.00469**	
		(0.00210)			(0.00191)	
Innovation quality			−0.0373			−0.0492*
			(0.0239)			(0.0266)
R&D personnel	0.471***	0.473***	0.387***	−0.0362	−0.0328	−0.0178
	(0.0373)	(0.0372)	(0.0528)	(0.0423)	(0.0421)	(0.0600)
R&D intensity	−0.00270***	−0.00271***	−0.00317***	−0.00251***	−0.00253***	−0.00315***
	(0.000633)	(0.000639)	(0.000878)	(0.000621)	(0.000627)	(0.000910)
R&D subsidy history	0.573***	0.574***	0.469***	0.484***	0.485***	0.424***
	(0.0246)	(0.0246)	(0.0283)	(0.0259)	(0.0259)	(0.0300)
SOE	−0.296***	−0.296***	−0.287***	−0.298***	−0.298***	−0.295***
	(0.0206)	(0.0206)	(0.0276)	(0.0228)	(0.0227)	(0.0305)
Size	0.501***	0.500***	0.497***	0.499***	0.498***	0.494***
	(0.00675)	(0.00665)	(0.00825)	(0.00697)	(0.00695)	(0.00896)
Age	0.0317***	0.0317***	0.0386***	0.0427***	0.0427***	0.0462***
	(0.00196)	(0.00195)	(0.00297)	(0.00248)	(0.00246)	(0.00396)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−5.915***	−5.915***	−5.647***	−5.440***	−5.439***	−5.236***
	(0.0746)	(0.0742)	(0.0995)	(0.0802)	(0.0800)	(0.110)
Observations	91,687	91,687	44,104	67,416	67,416	34,604
Pseudo R^2	0.437	0.437	0.421	0.455	0.455	0.449

Standard error in parentheses, clustered at individual level; ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

[4]For the derivation of this model, see Shaver (1998).
[5]To save space, we do not report the results of the propensity score matching, application choice model or fixed effects model.

Table 2. Firms' application strategies.

Variables	Total outputs 1	Subsample Major 2	Minor 3	Innovation quality 4
Apply	1.847***	0.0565	1.790***	−0.196***
	(0.264)	(0.0838)	(0.250)	(0.0422)
R&D expense	−0.0320	−0.0124	−0.0196	0.0222***
	(0.0308)	(0.00985)	(0.0291)	(0.00529)
R&D employee	0.247***	0.0137	0.233***	−0.0209**
	(0.0546)	(0.0174)	(0.0517)	(0.00879)
Capacity	2.277***	1.198***	1.079***	0.103***
	(0.0554)	(0.0175)	(0.0525)	(0.00641)
Size	0.116***	0.0151*	0.101***	−0.0108**
	(0.0277)	(0.00879)	(0.0263)	(0.00456)
Age	−0.0128*	0.00285	−0.0156**	−0.0036***
	(0.00701)	(0.00222)	(0.00664)	(0.00112)
Constant	−2.785	−0.221	−2.564	1.276***
	(2.243)	(0.721)	(2.122)	(0.292)
Observation	19,374	19,374	19,374	7,512
abebe9	2942(35)***	5310(35)***	1326(35)***	528.9(35)****

Notes: see Table 1.

The above results imply that firms adopt an application strategy of trading quality for quantity. Since measuring the value of patents is difficult for the government, it may consider applicants with a large number of patents to be highly innovative and thus subsidize their R&D activities, which enables fraudulent firms to obtain public R&D resources at a lower cost. However, firms' misleading signal distorts the allocation of public R&D resources and further weakens the effect of subsidies. Meanwhile, the imperfect selection process may lead to competition for subsidies between applicants, which is in pursuit of innovation output rather than true innovation ability.

V. Conclusion

This paper explored the application strategy of firms for selective R&D subsidies and found that applicants tend to increase their R&D outputs as a signal of being highly innovative, even if it comes at the expense of reducing the quality of innovation, while the government might not be able to distinguish imposters from truly innovative firms.

The empirical findings in this paper suggest the need for a more rigorous screening and supervision process. In addition, the screening process could be improved by focusing more on the technological progress and potential social benefit of a firm's R&D activities instead of indicators such as the number of patents and R&D investment.

Disclosure statement

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References

Aguirre, I., and A. Beitia. 2017. "Modelling Countervailing Incentives in Adverse Selection Models: A Synthesis." *Economic Models* 62: 82–89. doi:10.1016/j.econmod.2017.01.007.

Boeing, P. 2016. "The Allocation and Effectiveness of China's R&D Subsidies - Evidence from Listed Firms." *Research Policy* 45 (9): 1774–1789. doi:10.1016/j.respol.2016.05.007.

Cheung, K. Y., and P. Lin. 2004. "Spillover Effects of FDI on Innovation in China: Evidence from the Provincial Data." *China Economic Review* 15 (1): 25–44. doi:10.1016/S1043-951X(03)00027-0.

Dai, X., and F. Wang. 2019. "Does the High- and New-technology Enterprise Program Promote Innovative Performance? Evidence from Chinese Firms." *China Economic Review* 57: 1–20. doi:10.1016/j.chieco.2019.101330.

Howell, A. 2017. "Picking 'Winners' in China: Do Subsidies Matter for Indigenous Innovation and Firm Productivity? China Econ." *Review* 44: 154–165.

Li, J., Q. Su, and K. K. Lai. 2019. "The Research on Abatement Strategy for Manufacturer in the Supply Chain under Information Asymmetry." *Journal of Cleaner Production* 236: 117514. doi:10.1016/j.jclepro.2019.06.345.

Luo, S., and Y. 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.

Shaver, J. M. 1998. "Accounting for Endogeneity When Assessing Strategy Performance: Does Entry Mode Choice Affect FDI Survival? Manage." *Science* 44: 571–585.

Zhao, C., Z. Liu, J. C. Suárez Serrato, and D. Y. Xu. 2018. "Notching R&D Investment with Corporate Income Tax Cuts in China." In *Nber Work. Pap*, 1–66.