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State Ownership, Political Connection, and Innovation Subsidies in China*

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Abstract: We examine how a firm's political connection measured by the membership of its CEO in the People's Congress (PC) or Chinese People's Political Consultative Conference (CPPCC) influences its likelihood of receiving the innovation subsidies given by the state. We find that politically connected firms are more likely to receive innovation subsidies. The political connection measured in this way is found much more important than state ownership in explaining the allocation of innovation subsidies. We also investigate if the firms that receive innovation subsidies are more innovative, productive, or profitable. Our results show that the firms that receive innovation subsidies file and receive more patents, but that their patents are not necessarily of high quality. They do not have higher productivity or profitability, either. The results collectively suggest politically induced inefficiency in the allocation of innovation subsidies in China.

Keywords: Innovation subsidies, state-owned enterprises, political connection, patents, allocation efficiency

JEL Classification Codes: O31, O38, G38, P26

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1. Introduction

Over the last four decades, the Chinese economy has been moving from a command economy to a market economy (Lardy, 2014). During the transition, the nature of Chinese enterprises changed completely. Before China embarked on its economic reform in 1978, an industrial enterprise was just a tiny part of the state bureaucracy. After the reform started, these traditional State-owned Enterprises (SOEs) were gradually corporatized and restructured (Lin and Milhaupt, 2013; Naughton, 2018). Privately owned enterprises were allowed to enter the market and they started to grow, often much faster than many SOEs. Joint-venture firms with foreign capital were also established. Poorly performing SOEs eventually failed, while successful SOEs listed their shares on stock exchanges.

The declining share of SOEs in the economy, however, does not necessarily imply an improvement in efficiency and the rising role of markets. Privately owned enterprises may be able to capture the government and obtain a large amount of subsidies and/or ward off emerging (foreign) competitors. The government may be able to interfere with resource allocation without owning the enterprises, too. This is especially the case in China.

As is pointed out by Milhaupt and Zhang (2015), privately owned enterprises in China are different from privately owned firms in a typical market economy in several aspects. First, top managers of many private firms are current or former members of central or local state/party organizations such as People's Political Consultative Conferences. Second, many private firms receive large subsidies from the state. Third, private firms face extralegal state interventions well beyond the economic regulations that are also present in other market economies.

The tight connection between the "private" sector and the state/party is still a defining characteristic of Chinese capitalism. Thus, despite the decline of state ownership, the Chinese economy continues to be distant from a typical market economy. Nevertheless, many past studies focused exclusively on state ownership and did not pay attention to the other connections between the state and the privately owned firms that distort resource allocation. Moreover, some careful studies including Naughton (2018) and Lardy (2019) show that the distortionary state interventions have been rather increasing after around 2007.

This paper sheds further light on Chinese state capitalism by examining two distinct characteristics of corporate governance, namely still strong state ownership and political connection of private firms, and their implications. We use the data from the China Employer Employee Survey (CEES), which covers not only listed firms but also many unlisted firms, and study how state ownership and political connection are correlated with the allocation and success of subsidies that aim to encourage innovation.

More specifically, we examine what type of firms are more likely to receive the innovation subsidies and if the subsidized firms are more likely to be innovative (measured by the number of patents and the likelihood of introducing new products), productive, and profitable. Did firms that seem more likely to innovate receive innovation subsidies? Or were the subsidies allocated mainly to State-Owned Enterprises (SOEs) and other politically connected firms? Were subsidized firms more likely to succeed in innovating? These are the questions that we ask in this paper.

The paper contributes to two areas of economic inquiry. First, the paper adds to the literature on the extent and the implications of state interventions in Chinese industries, which take various forms including state ownership and influence through political connections. In addition to Milhaupt and Zhang (2015), Naughton (2018), and Lardy (2019) which we referred to, numerous studies examine the implications of state ownership of firms in China.

Many papers find that the productivity of SOEs is much lower than that of non-SOEs (Brandt et al. 2013, for example). The productivity of the SOE sector appeared to have improved during the late 1990s and early 2000s when many small SOEs were restructured or privatized under the slogan "Grasp the Large, Let Go of the Small" (Brandt et al. 2012, Hsieh and Song 2015). The gap remained and more resources were allocated to SOEs, especially after the Global Financial Crisis of 2007-2009 (Brandt et al. 2020, Johansson and Feng 2016).

The number of papers that study political connections, another channel that the Chinese state can use to influence businesses, is relatively small. Some papers find that firms with political connections enjoy better access to government subsidies, higher stock market valuation, and/or higher profitability (Wu et al. 2012, Li and Cheng 2020, Feng et al. 2015, Wu and Cheng 2011). Some papers find the value of political connections mostly negative (Zhang and Truong 2019). Wu et al. (2012) find that the politically connected local SOEs have lower stock values and employ more surplus labor compared with other local SOEs.

Few papers examine state ownership and political connection at the same time. Johansson and Feng (2016) are an exception. In addition to finding that the post-GFC stimulus program allocated loans preferentially to SOEs, they also find that the non-SOEs with political connections did better than others without political connections in accessing bank credits. Our paper contributes by investigating both state ownership and political connections.

Second, our paper is also related to the literature on the effects of innovation subsidies of the Chinese government. Liu, Li, and Li (2016) study a sample of high-tech manufacturing firms in Jiangsu province and find that a firm that receives government subsidies tends to show high R&D investment, especially if the firm is relatively small and privately-owned. Fang *et al*. (2018) find that government innovation subsidies are positively associated with future innovation, especially after the anti-corruption campaign and departures of local government innovation officials. Dang and Motohashi (2015) estimate the effects of China's innovation subsidies on both patent quantity and quality. They find that these policy incentives increase the number of patents but deteriorate the quality measured by the scope of claims. Fang *et al.* (2020) find that patent subsidy programs sequentially implemented across Chinese provinces between 1999 and 2007 weakened the positive association between patents and productivity over time, suggesting the quality of patents has deteriorated.

Firm samples employed by these papers mainly come from the publicly listed firm database or the Annual Industrial Enterprise Survey Data by the National Bureau of Statistics of China, which consists of only large- and medium-sized firms. However, many innovation activities are conducted by small-sized firms. This paper adds to the literature on the relationship between innovation outcomes and government subsidies by utilizing a dataset that includes a variety of firms of different sizes. Moreover, this paper adds to this strand of literature by distinguishing the specific types of patents to identify the quality of innovation incentivized by government subsidies.

The paper is organized in the following way. The next section introduces the Chinese

Employer Employee Survey (CEES), which is the database that we use to examine how the state ownership and political connection of firms influence the allocation and impacts of innovation subsidies. Section 3 reports the statistical analysis of the allocation of innovation subsidies. In Section 4, we investigate the robustness of our main results in Section 3. Section 5 considers the possibility that the influences of state ownership and political connection change over time and across firm size or performance. Section 6 examines what type of activities that subsidized firms undertook. Section 7 concludes.

2. Data

The data used in this study come from the China Employer Employee Survey (CEES), which is a collaborative project between Wuhan University, Hong Kong University of Science and Technology, Stanford University, and the Chinese Academy of Social Science (Chen and Hu, 2023). It began in 2015 with a survey of manufacturing firms and workers in the southeastern coastal province of Guangdong, and expanded to the central province of Hubei in 2016, and then to the eastern coastal province of Jiangsu, the western interior province of Sichuan, and the northeastern province of Jilin in 2018, aiming to represent the whole country.

In the 2015 and 2016 waves, we use the Third National Economic Census, which was conducted in early 2014, as our sampling frame. In 2018, a slightly varied sampling procedure was employed for the provinces that had been included in the previous waves as well as those that were newly introduced.

For the two previously surveyed provinces, Hubei and Guangdong, we first followed up with all the firms that we contacted in the previous two waves. To increase the coverage, we then pulled additional firms from the National Enterprise Registration Database administrated by the State Administration for Market Regulation, which covers all the firms at the end of 2016 in China. We added small firms ($10 \leq$ employees < 20) that were registered before 2013 but not sampled in the previous waves. We also added newly registered firms between 2014 and 2016.

For the newly added provinces, Jiangsu, Sichuan, and Jilin, all the samples come from the National Enterprise Registration Database, and sampling was conducted in two stages, each using probability proportionate-to-size (PPS) sampling, with a size defined as the number of employees involved in manufacturing. Thus, the firm sample is representative of the employment size of manufacturing firms in China. In the first stage, around 20 county-level districts were randomly sampled in each province, with probabilities proportional to manufacturing employment in each district. In the second stage, 50 firms were sampled in each district as a target sample, again with probabilities proportional to employment in each firm. For each of the 50 firms in a random order, an enumerator checked if it has production operation at the address by contacting government officials in the district or by visiting the firm directly. If the firm turns out to have a production operation, the enumerator collects the responses to the questionnaire. This process continued until the total number of respondents reaches 36 or all the 50 firms are contacted.

In this paper, we focus on the 2018 data which covers around 2000 firms across 99 counties in the five provinces, since it includes well-defined information on innovation subsidy, which is one of the main variables in our statistical analysis. The questionnaire asks each firm to provide all the subsidies received from different levels of government for financing research and development (R&D) activities. These innovation subsidies include not only direct subsidies, but also indirect subsidies from preferential tax rates, tax breaks, grants, and concessional loans that are earmarked for R&D activities. Each firm was asked to report the amount of innovation subsidies it received in each year of 2015, 2016, and 2017. This allows us to construct a three-year panel dataset.

In examining the allocation of innovation subsidies, a key question is whether the subsidies are allocated primarily to the firms that show greater promise to be innovative or to those firms that are politically favored. One way to define politically favored firms is to use the ownership by the state. CEES has information on state ownership of each firm as of 2017, and we define a state-owned enterprise (SOE) to be a firm that is majority-owned by the state. Note that the ownership variable is available only for one year while the innovation subsidies are observed for each of the three years (2015, 2016, and 2017).

State ownership is one way that a firm is politically favored, but there are some other channels that firms can use to be close to the government. As Li et al. (2006) point out, the Chinese political system consists of four branches. People's Congress (PC) is the legislative branch, (central and local) governments are the administrative branch, Supreme Court and People's Courts at local levels form the judicial branch, and the Chinese People's Political Consultative Conference (CPPCC) is the democratic supervision branch. Chinese firms can establish political connections with the government by acquiring seats for their CEOs in PC or CPPCC. Thus, we use the CEO's or the boss's ("一把手" in Chinese) membership in PC or CPPCC as another measure of political favors. We consider a firm politically connected if the CEO or the boss of the firm is a member of PC or CPPCC (national or local level). The political connection is observed only for one year (2017).

To investigate the association between innovation subsidies and the innovative activities of corporations, we examine the information regarding patents received by each firm in CEES. First, we use the total number of patents newly granted in each year between 2015 and 2017 (patent flow) and the total number of patents at the end of each year (patent stock). To alleviate the issue of time lags between innovation and patent approval, we also use data on the number of patent applications during each year, rather than granted patents. Second, we distinguish between patents granted in foreign countries and those in China for both flow and stock. The patents granted abroad are considered to have much higher quality than those granted in China since the Chinese patent system allows some marginal innovations and design tweaks. Third, we also examine the number of invention patents granted by the Chinese patent system. Invention patents are considered to have the highest quality among the three types of patents (the others are utility model patents and design patents). Examination of an invention patent involves checking the substance of utility, novelty, and non-obviousness, and takes a much longer time than the other types of patents. According to the Patent Annual Report by the State Intellectual Property Office of China, in 2016, among total patents in force (3,464,824, stock number), invention patents account for only 28.2%.

This paper also examines the association between innovation subsidies and corporate performance. The measures of corporate performance that we consider are grouped into two types: (1) productivity and (2) profitability. We use two measures of productivity. One is labor productivity, which is calculated by dividing the value added by the number of employees. The other is total factor productivity (TFP), which is calculated as follows. First, we estimate a value-added-based production function for each industry. Then, we calculate the total factor productivity for each firm, using the parameters estimated at the industry level. We follow the approach developed by Levinsohn and Petri (2003) to correct for potential bias in the estimation of production function caused by the correlation between productivity shocks and changes in input use. The profitability measure is a dummy variable that takes the numeric one when a firm has a loss in a given year.

Finally, we include several control variables in our regression analyses of innovation subsidy allocation, innovation outcome, and economic performance. They are firm age, number of employees (in log), firm's export status (0-1 variable that takes 1 for an exporting firm), skill intensity (the share of technicians and designers in a firm's total employment), CEO's age, and CEO's education level (number of years in school).

Summary statistics of the variables used in our analyses are reported in Table 1. Note that the state ownership and political connection variables are defined only for 2017. Thus, the number of observations for those variables is about 1/3 of those for the other variables. The table shows that only 6.7% of the firms in our sample are majority-owned by the state, but 23.8% of the firms are politically connected; 16% of the firms have their CEOs or owners in PC and 12.5% have CEOs or owners in CCPPC.

Table 1 also includes summary statistics of R&D investment conducted by the sample firms. In a robustness check that we report in Section 4, we use the R&D variable to account for potential heterogeneity in the ability and propensity to generate patentable innovations that are not captured by our control variables. An obvious problem of using R&D investment as an explanatory variable in the regressions is its endogeneity. A firm that receives an innovation subsidy may be more likely to conduct R&D investment. To avoid such an endogeneity problem, we do not include R&D investment in the main specifications of our regression model. We use the R&D investment variable only to check the robustness of our results.

Table 1. Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
SOE	1,785	0.067	0.250	0	1
Political connection					
PC	1,795	0.160	0.367	0	1
CPPCC	1,795	0.125	0.331	0	1
PC or CPPCC	1,795	0.238	0.426	0	1
Innovation subsidy					
Innovation subsidy dummy	5,330	0.149	0.356	0	1
Amount of innovation subsidies (10,000 Yuan)	5,330	57.83	578.67	0	17,029
Patent stock (Total number of patents)					
Total	5,330	21	169	0	6,060
Chinese	5,330	19	158	0	6,060
Chinese invention	5,330	4	25	0	725
Foreign	5,330	0	3	0	166
Patent flow (Newly granted patents)					
Total	5,330	3	31	0	1,128
Chinese	5,330	3	29	0	1,128
Chinese invention	5,330	1	4	0	106
Foreign	5,330	0	1	0	63
Performance					
Value-added per capita in log	5,330	2.07	1.90	-8.59	11.27
TFP in log	5,330	2.18	1.88	-6.09	14.44
Have a loss	5,330	0.192	0.394	0	1
Firm's attributes					
Firm age (Year)	1,805	14	9	1	81
Employment (Person)	5,330	498	1,589	5	26,001
Export	1,794	0.362	0.481	0	1
Skill intensity	5,267	7.08	8.38	0	92.86
R&D investment (10,000 Yuan)	5,330	883.06	6,251.35	0	277,365
Entrepreneur's attributes					
Age	1,791	50	9	20	81
Years of schooling	1,799	14	3	0	22

Notes: Results are calculated at the firm-year level. SOE, Political connection, Firm age, Export, Entrepreneur's age, and Entrepreneur's years of schooling are cross-sectional variables.

Political connections can also be endogenous. A firm may develop political connections as a result of receiving government subsidies. We address this concern also in

Section 4 by using a sub-sample of the firms that were included in both the 2016 and 2018 waves. For these firms, we observe their political connections not only in 2017 but also in 2015. Thus, we can check how serious the endogeneity problem is.

Another concern is that the observed relationship between political connections and innovation subsidies may be driven by the general success of the firm, which affects both the CEO's membership in PC (or CCPPC) and receiving subsidies.[1] Our controls may not be able to fully capture such general success of the firms. To deal with this type of endogeneity issue we try two approaches as we explain below: adding the value-added per worker as an additional control and employing the instrumental variable (IV) approach using the presence of a trade union as an instrument.

Table 2 shows a cross-tabulation of the political connection and the state ownership. The majority of the firms in our sample (1,228 firms or 71.6% of the sample) are not state-owned and have no political connections. A small number of firms (33 firms or 1.9% of the sample) are state-owned and have political connections. There are some SOEs (75 or 4.4% of the sample) that are not politically connected according to our definition. Finally, there is a substantial number of non-SOEs (379 or 22.1% of the sample) that are politically connected.

Table 2. Political connection and state ownership

	Without Political Connection		With Political Connection		Total	
	Obs.	Row %	Obs.	Row %	Obs.	Row %
Non-SOEs	1,228	76.4	379	23.6	1,607	100
SOEs	75	69.4	33	30.6	108	100
Total	1,303	76.0	412	24.0	1,715	100

Notes: Results are calculated by using the firm's information in the year 2017.

[1] We thank the anonymous referee for pointing out this potential problem.

3. Allocation of Innovation Subsidy

This section examines whether state ownership and political connection matter for the likelihood of receiving innovation subsidies. Table 3 classifies the firms into four groups according to state ownership (state-owned or not) and political connection (politically connected or not). For each group, the table shows the number of firms that belong to the group and the proportion of firms that receive innovation subsidies among them. For example, there are 33 firms that are state-owned and politically connected and 39% of them received innovation subsidies in at least one year between 2015 and 2017. The last column reports the difference in the proportion of firms that receive innovation subsidies between SOEs and non-SOEs, and the last row reports the difference between firms with political connections and those without connections. The numbers in parentheses are standard errors. For firms with political connections, the proportion of firms that receive innovation subsidies is 11.4% higher for SOEs than non-SOEs. For firms without political connections, the difference is smaller (4.5%). Neither of these differences is statistically significant. For SOEs, the proportion of firms that receive innovation subsidies is 19.4% higher for firms with political connections than those without political connections and the difference is statistically significant. For non-SOEs, the difference is smaller (12.5%) but still statistically significant. Thus, the table shows that political connection seems to matter for the allocation of innovation subsidies. Politically connected firms are more likely to receive innovation subsidies than those without such connections. The table also shows that SOEs are more likely to receive innovation subsidies than non-SOEs, but the difference is not statistically significant.

Table 3. The proportion of firms that receive innovation subsidies by ownership and political connection

	SOEs		Non-SOEs		Mean difference (S.E.)
	# of Obs.	Mean	# of Obs.	Mean	
With political connection	33	0.394	379	0.280	0.114 (0.082)
Without political connection	75	0.200	1,228	0.155	0.045 (0.043)
Mean difference (S.E.)	0.194** (0.090)		0.125*** (0.023)		

Notes: Firms with innovation subsidies are those that once obtained innovation subsidies in any year between 2015 and 2017. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are in parentheses.

Table 4 reports a similar calculation using the amount of innovation subsidies. In the table, each cell now reports the average of the natural log of the firm average of the amount of innovation subsidies over the sample years (2015-2017) plus 1. The result suggests that SOEs and politically connected firms receive a larger amount of innovation subsidies on average than non-SOEs and firms without political connections respectively.

Table 4. The amount of innovation subsidies by state ownership and political connection

	SOEs		Non-SOEs		Mean difference (S.E.)
	# of Obs.	Mean	# of Obs.	Mean	
With political connection	33	1.935	379	1.100	0.834** (0.374)
Without political connection	75	0.992	1,228	0.545	0.446** (0.178)
Mean difference (S.E.)	0.943* (0.488)		0.555*** (0.094)		

Notes: The amount of innovation subsidies in log is calculated by adding 1 to the average amount of innovation subsidies during 2015 and 2017 and then taking the logarithm. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are in parentheses.

The descriptive results in Tables 3 and 4 are suggestive, but the simple comparison does not prove that these firms receive more innovation subsidies because of their relation to the government. Politically connected firms may be different from non-politically connected firms in various attributes such as size and quality of workers, and those differences may influence the likelihood of receiving innovation subsidies.

We address this concern by estimating multivariate regression models that control for various firm attributes other than political connection and state ownership that may influence the firm's likelihood of receiving innovation subsidies. The dependent variable is the innovation subsidy dummy or the amount of innovation subsidies received by the firm. As the explanatory variables in addition to the state ownership and political connection, we include firm age, the number of employees in log, export dummy, skill intensity, CEO's age, and CEO's years of schooling. We also include 2-digit industry dummies and province dummies to control for the industry-specific and region-specific effects, such as different innovation policies. Standard errors are clustered at the county level for all regressions.

Table 5 presents the estimation results for the determination of the allocation of innovation subsidies across firms using the innovation subsidy dummy as the dependent variable. In Column 1, when the specification includes just industry dummies and province dummies, SOEs are 6.3% more likely to obtain innovation subsidies, but the estimate is not statistically significant. Other researchers found that SOEs are more likely to get innovation subsidies (König et al., 2020; Tan et al., 2016; Herrala and Jia, 2015; Ferri and Liu, 2010). However, our estimate is not statistically significant even in the simple specification. Thus, majority state ownership is not correlated with the likelihood of getting innovation subsidies.

Columns 4, 5, and 6 report the estimation results for specifications with the political connection dummy. It is found that the political connection increases the probability of receiving innovation subsidies. When the set of control variables is added (Columns 5 and 6), the coefficient estimate on the political connection dummy becomes smaller but remains statistically significant. The point estimate in Column 6 suggests that having political connections increases the probability of receiving innovation subsidies by 8.4%. Since only 14.9% of the sample received innovation subsidies during 2015 and 2017, the estimated impact of political connection is economically significant.

Columns 7, 8, and 9 include both political connection and SOE dummies as explanatory variables. Consistent with the results in columns 1 through 6, the political connection dummies enter the regression model with positive signs, while the SOE dummy does not matter for the likelihood of receiving innovation subsidies.

Columns 10, 11, and 12 add the interaction term of political connection and SOE. The positive and significant coefficient on the political connection dummy confirms the importance of political connection for non-SOEs. To calculate the impact of political connection for SOEs, we need to add the coefficient on the political connection dummy and that on the interaction term. The coefficient on the interaction term is positive but its standard error is large. In the specification in Column 12, for example, the sum of the two coefficient estimates is 0.131 and not statistically significant.[2] Thus, for SOEs, the result of the positive impact of political connections on the likelihood of obtaining innovation subsidies is not statistically significant.

Table 6 reports the specifications with the amount of innovation subsidies (in log) as the dependent variable. The results are very similar to the ones in Table 5. In the simplest specification, SOEs receive 56.5% more innovation subsidies than non-SOEs (Column 1), and

[2] The Wald test for the difference yields F-statistic of 2.56 and p-value of 0.113.

politically connected firms receive 63.2% more than non-politically connected firms (Column 4). When the control variables are added, the difference in the amount of innovation subsidies received between SOEs and non-SOEs becomes much smaller and insignificant (Columns 2 and 3), while the difference between politically connected firms and non-politically connected firms remains significant. Politically connected firms receive about 35% more than non-politically connected firms (Columns 5 and 6). When both state-ownership and political connection are included in the specification with all the control variables, the political connection remains statistically significant while the state ownership does not influence the amount of innovation subsidies significantly (Column 9). The coefficient on the interaction term between the state ownership and the political connection is estimated to be positive but not statistically significant (Column 12).

Taken together, the results in Tables 5 and 6 suggest that the innovation subsidies are more likely to be allocated to politically connected non-SOEs when the relevant observable characteristics are controlled for. Unless the political connection is perfectly correlated with the capacity to innovate, the result means that there exist some firms that do not receive the innovation subsidies but have a higher capacity to innovate than those firms that receive the subsidies because of their political connection. In this sense, innovation subsidies are allocated inefficiently.

Table 5. OLS regressions of innovation subsidy dummy on ownership and political connection

	Innovation subsidy dummy											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SOE	0.063	-0.031	-0.032				0.063	-0.024	-0.025	0.047	-0.040	-0.041
	(0.041)	(0.037)	(0.037)				(0.041)	(0.037)	(0.037)	(0.049)	(0.048)	(0.047)
Political connection				0.136***	0.085***	0.084***	0.136***	0.085***	0.084***	0.132***	0.081***	0.080***
				(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.026)	(0.026)
SOE*Political connection										0.053	0.050	0.051
										(0.090)	(0.085)	(0.085)
Firm age		0.001	0.001		0.001	0.000		0.001	0.001		0.001	0.001
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Employment in log		0.064***	0.062***		0.058***	0.057***		0.059***	0.058***		0.059***	0.058***
		(0.008)	(0.008)		(0.008)	(0.008)		(0.008)	(0.008)		(0.008)	(0.008)
Export		0.030	0.029		0.027	0.027		0.027	0.026		0.026	0.026
		(0.024)	(0.024)		(0.024)	(0.024)		(0.024)	(0.024)		(0.024)	(0.024)
Skill intensity		0.005***	0.005***		0.005***	0.005***		0.005***	0.005***		0.005***	0.005***
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Age			0.001			0.001			0.001			0.001
			(0.001)			(0.001)			(0.001)			(0.001)
Years of schooling			0.001			0.001			0.001			0.001
			(0.003)			(0.003)			(0.003)			(0.003)
2-digit industry	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-Squared	0.073	0.148	0.148	0.092	0.155	0.155	0.093	0.155	0.155	0.093	0.155	0.156
Observations	1,715	1,715	1,715	1,715	1,715	1,715	1,715	1,715	1,715	1,715	1,715	1,715

Notes: The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in any year between 2015 and 2017. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

Table 6. OLS regressions of the amount of innovation subsidies in log on ownership and political connection

	Amount of innovation subsidies in log											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SOE	0.565**	0.048	0.047				0.566**	0.076	0.074	0.460*	-0.026	-0.028
	(0.238)	(0.193)	(0.193)				(0.234)	(0.194)	(0.193)	(0.264)	(0.241)	(0.241)
Political connection				0.632***	0.349***	0.348***	0.632***	0.351***	0.350***	0.606***	0.326***	0.325***
				(0.111)	(0.104)	(0.105)	(0.112)	(0.105)	(0.106)	(0.115)	(0.111)	(0.111)
SOE*Political connection										0.352	0.340	0.341
										(0.470)	(0.423)	(0.423)
Firm age		0.004	0.004		0.004	0.004		0.004	0.003		0.003	0.003
		(0.005)	(0.005)		(0.005)	(0.005)		(0.005)	(0.005)		(0.005)	(0.005)
Employment in log		0.357***	0.353***		0.339***	0.336***		0.337***	0.334***		0.337***	0.335***
		(0.045)	(0.048)		(0.043)	(0.046)		(0.044)	(0.047)		(0.044)	(0.047)
Export		0.088	0.086		0.072	0.070		0.073	0.072		0.072	0.071
		(0.092)	(0.092)		(0.092)	(0.091)		(0.092)	(0.091)		(0.091)	(0.090)
Skill intensity		0.028***	0.028***		0.028***	0.028***		0.028***	0.028***		0.028***	0.028***
		(0.006)	(0.006)		(0.006)	(0.006)		(0.006)	(0.006)		(0.006)	(0.006)
Age			0.002			0.001			0.001			0.001
			(0.004)			(0.004)			(0.004)			(0.004)
Years of schooling			0.001			0.003			0.002			0.002
			(0.013)			(0.013)			(0.013)			(0.013)
2-digit industry	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-Squared	0.077	0.198	0.198	0.095	0.205	0.205	0.101	0.205	0.205	0.102	0.206	0.206
Observations	1,715	1,715	1,715	1,715	1,715	1,715	1,715	1,715	1,715	1,715	1,715	1,715

Notes: The amount of innovation subsidies in log is calculated by adding 1 to the average amount of innovation subsidies during 2015 and 2017 and then taking the logarithm. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

4. Robustness Checks

4.1. Propensity Score Matching

Another way to control for the various firm attributes other than political connections that may influence the likelihood of receiving innovation subsidies is to repeat the comparisons in Tables 3 and 4 for the firms that differ only in the political connection variables. Tables 7 and 8 report the results of such comparison exercises using propensity score matching (Rosenbaum and Rubin, 1983). We start by estimating a logit model that describes the probability that a firm receives the innovation subsidy as a function of some observable characteristics. For such firm characteristics, here we consider the firm age, the number of employees (in log), a dummy variable that shows if the firm exports its products or not, the skill intensity of workers, and the age and the years of schooling for the CEO. We also include industry and provincial dummies in the logit model. The estimated model gives us a propensity score for each firm. Then, we match each firm that receives the innovation subsidy to the firms that do not receive the subsidy but have similar propensity scores by using the K-nearest neighbor matching method.[3] The results in Tables 7 and 8 show that state-ownership does not make a difference in the likelihood of getting the innovation subsidies. The political connection does not make a difference, either, for SOEs. For non-SOEs, however, the political connection is important for receiving innovation subsidies.

The results in Tables 7 and 8 are consistent with what we find in the regression

[3] This approach matches each firm that receives innovation subsidy with K firms that have the closest propensity scores but do not receive the subsidies. For the value of K, we consider every integer between 1 and 8.

analyses in Tables 5 and 6. State ownership does not influence the likelihood of getting innovation subsidies. The political connection does not matter for SOEs, but for non-SOEs, having a political connection is very useful in getting innovation subsidies.

Table 7. PSM estimation of the effect of state ownership

	With political connection			Without political connection		
	SOE	Non-SOE	Difference	SOE	Non-SOE	Difference
	Obs.=33	Obs.=379	(S.E.)	Obs.=75	Obs.=1,228	(S.E.)
Outcome: Innovation subsidy dummy						
ATT (k=1)	0.387	0.484	-0.097(0.156)	0.205	0.178	0.027(0.072)
ATT (k=2)	0.387	0.468	-0.081(0.129)	0.205	0.233	-0.027(0.066)
ATT (k=3)	0.387	0.516	-0.129(0.12)	0.205	0.224	-0.018(0.062)
ATT (k=4)	0.387	0.468	-0.081(0.116)	0.205	0.223	-0.017(0.06)
ATT (k=5)	0.387	0.471	-0.084(0.114)	0.205	0.227	-0.022(0.059)
ATT (k=6)	0.387	0.419	-0.032(0.111)	0.205	0.226	-0.021(0.058)
ATT (k=7)	0.387	0.396	-0.009(0.109)	0.205	0.237	-0.031(0.058)
ATT (k=8)	0.387	0.387	0(0.107)	0.205	0.241	-0.036(0.057)
Outcome: Amount of innovation subsidies in log						
ATT (k=1)	1.866	2.025	-0.16(0.799)	1.019	0.805	0.214(0.365)
ATT (k=2)	1.866	1.873	-0.007(0.637)	1.019	1.099	-0.08(0.339)
ATT (k=3)	1.866	2.034	-0.169(0.596)	1.019	1.049	-0.03(0.32)
ATT (k=4)	1.866	1.953	-0.087(0.587)	1.019	0.988	0.031(0.309)
ATT (k=5)	1.866	2.010	-0.144(0.583)	1.019	1.012	0.007(0.3)
ATT (k=6)	1.866	1.806	0.06(0.569)	1.019	0.997	0.022(0.296)
ATT (k=7)	1.866	1.683	0.183(0.559)	1.019	1.070	-0.051(0.294)
ATT (k=8)	1.866	1.682	0.184(0.554)	1.019	1.094	-0.075(0.294)

Note: K-nearest neighbor matching method is used when matching. Firms with innovation subsidies are those that once obtained innovation subsidies in any year between 2015 and 2017. The amount of innovation subsidies in log is calculated by adding 1 to the average amount of innovation subsidies during 2015 and 2017 and then taking the logarithm. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 8. PSM estimation of the effect of political connection

	SOE			Non-SOE		
	With political connection	Without political connection	Difference (S.E.)	With political connection	Without political connection	Difference (S.E.)
	Obs.=33	Obs.=75		Obs.=379	Obs.=1,228	
Outcome: Innovation subsidy dummy						
ATT (k=1)	0.355	0.194	0.161(0.194)	0.281	0.207	0.074**(0.036)
ATT (k=2)	0.355	0.194	0.161(0.157)	0.281	0.223	0.058*(0.032)
ATT (k=3)	0.355	0.290	0.065(0.159)	0.281	0.202	0.079***(0.03)
ATT (k=4)	0.355	0.266	0.089(0.148)	0.281	0.196	0.085***(0.03)
ATT (k=5)	0.355	0.284	0.071(0.145)	0.281	0.193	0.089***(0.029)
ATT (k=6)	0.355	0.258	0.097(0.137)	0.281	0.195	0.086***(0.029)
ATT (k=7)	0.355	0.226	0.129(0.132)	0.281	0.203	0.078***(0.029)
ATT (k=8)	0.355	0.210	0.145(0.128)	0.281	0.201	0.08***(0.028)
Outcome: Amount of innovation subsidies in log						
ATT (k=1)	1.723	0.897	0.826(0.892)	1.106	0.830	0.276**(0.158)
ATT (k=2)	1.723	0.986	0.737(0.81)	1.106	0.900	0.206(0.141)
ATT (k=3)	1.723	1.583	0.14(0.898)	1.106	0.816	0.29**(0.132)
ATT (k=4)	1.723	1.422	0.302(0.838)	1.106	0.792	0.314**(0.129)
ATT (k=5)	1.723	1.499	0.224(0.822)	1.106	0.763	0.343***(0.126)
ATT (k=6)	1.723	1.349	0.374(0.774)	1.106	0.772	0.334***(0.124)
ATT (k=7)	1.723	1.185	0.539(0.742)	1.106	0.790	0.316**(0.123)
ATT (k=8)	1.723	1.105	0.619(0.717)	1.106	0.775	0.332***(0.122)

Note: K-nearest neighbor matching method is used when matching. Firms with innovation subsidies are those that once obtained innovation subsidies in any year between 2015 and 2017. The amount of innovation subsidies in log is calculated by adding 1 to the average amount of innovation subsidies during 2015 and 2017 and then taking the logarithm. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

4.2. R&D Investment as an Explanatory Variable

The control variables in our regression models do not include R&D investment, which would be correlated with the firm's capacity to innovate. We do not use any R&D variable as an explanatory variable because we are concerned about the obvious reverse causality: a firm that receives innovation subsidies is more likely to conduct R&D investment. Here we report regression results with R&D investment to show our main finding is robust to the inclusion of an R&D variable.

Table 9. OLS regressions of innovation subsidy on ownership and political connection with additional control of R&D investment

	Innovation subsidy dummy		Amount of innovation subsidies in log	
	(1)	(2)	(3)	(4)
Political connection	0.051**	0.050**	0.217**	0.214**
	(0.021)	(0.021)	(0.095)	(0.095)
SOE	-0.023	-0.022	0.082	0.088
	(0.036)	(0.036)	(0.184)	(0.186)
Firm age	-0.000	-0.000	0.001	0.000
	(0.001)	(0.001)	(0.005)	(0.005)
Employment in log	0.007	0.007	0.127***	0.129***
	(0.007)	(0.008)	(0.036)	(0.038)
Export	0.003	0.004	-0.023	-0.019
	(0.022)	(0.023)	(0.086)	(0.085)
Skill intensity	0.002	0.002	0.015***	0.015***
	(0.001)	(0.001)	(0.005)	(0.005)
R&D investment in log	0.058***	0.058***	0.234***	0.235***
	(0.004)	(0.004)	(0.018)	(0.018)
Age		0.001		0.001
		(0.001)		(0.004)
Years of schooling		-0.001		-0.005
		(0.002)		(0.012)
2-digit industry	Y	Y	Y	Y
Province	Y	Y	Y	Y
R-Squared	0.268	0.268	0.306	0.307
Observations	1,715	1,715	1,715	1,715

Notes: The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in any year between 2015 and 2017. The amount of innovation subsidies in log is calculated by adding 1 to the average amount of innovation subsidies during 2015 and 2017 and then taking the logarithm. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

Table 9 shows regression results with R&D investment (in log) as an explanatory variable. Columns 1 and 2 of Table 9 correspond to Columns 8 and 9 of Table 5, and Columns 3 and 4 of Table 9 correspond to Columns 8 and 9 of Table 6. In all the specifications reported in Table 9, the coefficient estimates on the R&D variable are positive and statistically significant. The coefficient estimates on the political connection become somewhat smaller, but they are still statistically significant at the 5% level. Thus, our main finding remains qualitatively the same even when we include R&D investment as an explanatory variable.

4.3. Endogeneity of Political Connection

Our finding of the importance of political connection is based on the analysis using our measure of political connection in 2017. Since our dependent variable, such as the innovation subsidy dummy, is also measured in 2017, the regression can suffer from the endogeneity of the independent variable (political connection). It is possible that a firm develops political connections as a result of receiving government subsidies.

Fortunately, our dataset includes information on the political connection as of 2015 for a subset of the firms that participated in both the 2016 and 2018 waves of the CEES. Table 10 shows how the political connection measured during the 2018 wave is related to the one measured in the 2016 wave for those firms that responded to both waves of the survey. For the majority of the firms (410 out of 511), the political connection variable did not change between the 2016 and 2018 waves. About 20% of the firms saw their political connections change between 2016 and 2018. 44 firms that did not have political connections in 2016 gained political connections in 2018, while 57 firms lost political connections that they had in 2016 by 2018.

Table 10. Political connections of the tracked firms

	Wave 2018

		Without	With	Total
Wave 2016	Without	339	44	383
	With	57	71	128
	Total	396	115	511

Notes: Samples are restricted to firms surveyed in both waves and with non-missing values of political connections in both waves.

Table 11 shows the result of replicating some regressions in Tables 5 and 6 for the subsample that includes only the firms that participated in both the 2016 and 2018 waves of the CEES. Table 12 shows the result of the same exercise for the rest of the firms in the sample (firms that participated in the 2018 wave only). In both tables, Columns 1, 2, and 3 replicate the regressions in Columns 4, 8, and 9 of Table 5, and Columns 4, 5, and 6 replicates the regressions in Columns 4, 8, and 9 in Table 6. Comparing Table 11 to Table 12, we find the results are qualitatively similar, although the coefficient estimates on the political connection variable are slightly higher for Table 11. For both subsamples, the firms with political connections (in 2017) are found to be more likely to receive innovation subsidies. Thus, we confirm that the firms that participated in both waves of CEES are not very different from the firms that participated only in the 2018 wave.

With this background, we estimate the regressions using the political connection in 2015 for the subsample that participated in both waves. The result is reported in Table 13. We find the coefficient estimates on the political connection are statistically significant and only slightly smaller than those in Table 11. The result suggests that there may be some degree of the endogeneity problem, but it is not large enough to change the main conclusion that politically connected firms are more likely to receive innovation subsidies.

Table 11. OLS regressions of innovation subsidy dummy on ownership and political connection for tracked samples

	Innovation subsidy dummy			Amount of innovation subsidies in log		
	(1)	(2)	(3)	(4)	(5)	(6)
Political connection	0.166***	0.101**	0.102**	0.894***	0.532**	0.536**
(in 2017)	(0.046)	(0.047)	(0.048)	(0.256)	(0.229)	(0.235)
SOE		0.073	0.066		0.804	0.815
		(0.125)	(0.121)		(0.589)	(0.580)
Firm age		0.002	0.002		0.017	0.018
		(0.003)	(0.003)		(0.011)	(0.011)
Employment in log		0.069***	0.066***		0.375***	0.380***
		(0.013)	(0.015)		(0.077)	(0.087)
Export		0.035	0.032		0.093	0.099
		(0.037)	(0.037)		(0.166)	(0.158)
Skill intensity		0.007***	0.007**		0.051***	0.051***
		(0.003)	(0.003)		(0.012)	(0.012)
Age			-0.000			-0.001
			(0.002)			(0.008)
Years of schooling			0.005			-0.007
			(0.005)			(0.028)
2-digit industry	Y	Y	Y	Y	Y	Y
Province	Y	Y	Y	Y	Y	Y
R-Squared	0.140	0.228	0.229	0.153	0.333	0.333
Observations	511	511	511	511	511	511

Notes: Political connection is for the status of a firm in 2017. The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in any year between 2015 and 2017. The amount of innovation subsidies in log is calculated by adding 1 to the average amount of innovation subsidies during 2015 and 2017 and then taking the logarithm. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

Table 12. OLS regressions of innovation subsidy dummy on ownership and political connection for samples excluding tracked firms

	Innovation subsidy dummy			Amount of innovation subsidies in log		
	(1)	(2)	(3)	(4)	(5)	(6)
Political connection	0.117***	0.078***	0.076**	0.474***	0.253**	0.252**
(in 2017)	(0.028)	(0.029)	(0.029)	(0.114)	(0.118)	(0.118)
SOE		-0.053	-0.050		-0.114	-0.113
		(0.038)	(0.038)		(0.176)	(0.180)
Firm age		0.000	0.000		0.000	-0.000
		(0.001)	(0.001)		(0.005)	(0.005)
Employment in log		0.052***	0.052***		0.310***	0.309***
		(0.010)	(0.010)		(0.053)	(0.054)
Export		0.023	0.025		0.046	0.047
		(0.031)	(0.031)		(0.115)	(0.115)
Skill intensity		0.004***	0.004***		0.018***	0.018***
		(0.001)	(0.001)		(0.006)	(0.006)
Age			0.001			0.001
			(0.001)			(0.005)
Years of schooling			-0.002			-0.000
			(0.003)			(0.012)
2-digit industry	Y	Y	Y	Y	Y	Y
Province	Y	Y	Y	Y	Y	Y
R-Squared	0.101	0.147	0.147	0.102	0.181	0.181
Observations	1,204	1,204	1,204	1,204	1,204	1,204

Notes: Political connection is for the status of a firm in 2017. The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in any year between 2015 and 2017. The amount of innovation subsidies in log is calculated by adding 1 to the average amount of innovation subsidies during 2015 and 2017 and then taking the logarithm. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

Table 13. OLS regressions of innovation subsidy dummy on ownership and political connection for tracked samples

	Innovation subsidy dummy			Amount of innovation subsidies in log		
	(1)	(2)	(3)	(4)	(5)	(6)
Political connection	0.147***	0.093**	0.094**	0.719***	0.378**	0.387**
(in 2015)	(0.041)	(0.041)	(0.044)	(0.211)	(0.171)	(0.180)
SOE		0.066	0.059		0.764	0.776
		(0.123)	(0.119)		(0.572)	(0.562)
Firm age		0.001	0.001		0.014	0.015
		(0.003)	(0.003)		(0.011)	(0.011)
Employment in log		0.071***	0.069***		0.388***	0.394***
		(0.014)	(0.015)		(0.080)	(0.091)
Export		0.044	0.041		0.142	0.149
		(0.035)	(0.035)		(0.158)	(0.151)
Skill intensity		0.007***	0.007***		0.051***	0.052***
		(0.002)	(0.002)		(0.012)	(0.012)
Age			-0.001			-0.002
			(0.002)			(0.008)
Years of schooling			0.004			-0.009
			(0.005)			(0.029)
2-digit industry	Y	Y	Y	Y	Y	Y
Province	Y	Y	Y	Y	Y	Y
R-Squared	0.135	0.227	0.228	0.140	0.327	0.327
Observations	511	511	511	511	511	511

Notes: Political connection is for the status of a firm in 2015. The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in any year between 2015 and 2017. The amount of innovation subsidies in log is calculated by adding 1 to the average amount of innovation subsidies during 2015 and 2017 and then taking the logarithm. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

In addition to the aforementioned concern regarding potential reverse causality, the issue of omitted variable bias might also be present. This bias might emerge due to the possibility that both innovation subsidies and political connections could be influenced by a shared factor, which is the overall success of the firm. Although Section 4.2 considers the possibility that innovative firms (proxied by high R&D investment) happen to be more politically connected, it is important to note that R&D investment does not capture the general success of the firm. In the following, we try two additional approaches to deal with this type of endogeneity issue.

First, we re-run the regressions by adding the value-added per worker, which would be a more comprehensive measure of firm success, as an additional explanatory variable. The results are reported in Table 14. As we can see, even after incorporating value-added per worker as a control, the coefficient estimates on political connection are still statistically significant, indicating that political connection remains a significant factor influencing the receipt of innovation subsidies.

Second, following Guo et al. (2014), we employ the presence of a trade union within the firm as an instrument and apply an instrumental variable (IV) estimation. The rationale is that the existence of trade unions is closely associated with political connections, but it doesn't exhibit an obvious strong correlation with the firm's innovation performance, which could influence the firm's likelihood of receiving innovation subsidies. Table 15 presents the results and shows that the political connection that is explained by the existence of trade unions (and not by the firm success proxied by value-added per worker) is a very important determinant of innovation subsidies. The results underscore the robustness of our observation that politically connected firms are more likely to obtain innovation subsidies, even when accounting for potential omitted variable bias.

Table 14. OLS regressions of innovation subsidy on ownership and political connection with additional control of past productivity

	Innovation subsidy dummy		Amount of innovation subsidies in log	
	(1)	(2)	(3)	(4)
Political connection	0.084***	0.083***	0.347***	0.345***
	(0.024)	(0.024)	(0.105)	(0.105)
SOE	-0.026	-0.026	0.074	0.072
	(0.037)	(0.037)	(0.198)	(0.198)
Firm age	0.001	0.001	0.004	0.003
	(0.001)	(0.001)	(0.005)	(0.005)
Employment in log	0.059***	0.058***	0.337***	0.336***
	(0.008)	(0.008)	(0.044)	(0.047)
Export	0.025	0.025	0.065	0.064
	(0.024)	(0.024)	(0.094)	(0.092)
Skill intensity	0.005***	0.005***	0.027***	0.027***
	(0.001)	(0.001)	(0.006)	(0.006)
Value-added per capita in log	0.006	0.006	0.037*	0.037*
(in 2015)	(0.004)	(0.004)	(0.020)	(0.020)
Age		0.001		0.001
		(0.001)		(0.004)
Years of schooling		0.001		0.001
		(0.003)		(0.013)
2-digit industry	Y	Y	Y	Y
Province	Y	Y	Y	Y
R-Squared	0.156	0.156	0.207	0.207
Observations	1,715	1,715	1,715	1,715

Notes: The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in any year between 2015 and 2017. The amount of innovation subsidies in log is calculated by adding 1 to the average amount of innovation subsidies during 2015 and 2017 and then taking the logarithm. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

Table 15. Instrumental variable regressions of innovation subsidy on ownership and political connection

	Innovation subsidy dummy		Amount of innovation subsidies in log	
	(1)	(2)	(3)	(4)
	Second stage			
Political connection	0.691***	0.690***	1.677**	1.673**
	(0.224)	(0.224)	(0.817)	(0.817)
SOE	0.022	0.021	0.178	0.176
	(0.049)	(0.049)	(0.179)	(0.180)
Firm age	-0.000	-0.000	0.002	0.002
	(0.001)	(0.001)	(0.005)	(0.005)
Employment in log	0.025*	0.025*	0.262***	0.263***
	(0.015)	(0.015)	(0.054)	(0.054)
Export	0.001	0.001	0.018	0.011
	(0.028)	(0.028)	(0.103)	(0.103)
Skill intensity	0.005***	0.005***	0.026***	0.026***
	(0.001)	(0.001)	(0.005)	(0.005)
Age	-0.002	-0.002	-0.005	-0.005
	(0.002)	(0.002)	(0.006)	(0.006)
Years of schooling	0.002	0.002	0.004	0.004
	(0.004)	(0.004)	(0.013)	(0.013)
Value-added per capita in log (in 2015)		0.003		0.031
		(0.006)		(0.021)
	First stage			
Trade Union	0.112***	0.112***	0.112***	0.112***
	(0.023)	(0.023)	(0.023)	(0.023)
2-digit industry	Y	Y	Y	Y
Province	Y	Y	Y	Y
F statistics	23.157	23.114	23.157	23.114
Observations	1,715	1,715	1,715	1,715

Notes: The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in any year between 2015 and 2017. The amount of innovation subsidies in log is calculated by adding 1 to the average amount of innovation subsidies during 2015 and 2017 and then taking the logarithm. Only samples in the year 2017 are kept. The trade union is a dummy variable, taking a value of 1 to indicate the presence of a trade union within the firm. F statistics of the first stage is the Cragg-Donald Wald F statistics. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

5. Heterogeneous Effects

The analysis in Sections 3 and 4 assumes that the association between innovation subsidy and political connection does not vary with other characteristics such as firm size and firm performance. To relax this assumption, we split the sample according to these variables and estimate a regression model for each group.

Table 16. OLS regressions of innovation subsidy on ownership and political connection by firm size

	Innovation subsidy dummy		Amount of innovation subsidies in log	
	Small	Large	Small	Large
	(1)	(2)	(3)	(4)
Political connection	0.066	0.130***	0.180	0.680***
	(0.041)	(0.032)	(0.128)	(0.158)
SOE	0.021	-0.009	0.006	0.236
	(0.075)	(0.050)	(0.233)	(0.254)
Firm age	-0.000	0.001	-0.001	0.011
	(0.001)	(0.002)	(0.003)	(0.007)
Export	0.056**	0.032	0.124	0.248
	(0.026)	(0.036)	(0.079)	(0.151)
Skill intensity	0.004**	0.007***	0.012***	0.049***
	(0.002)	(0.002)	(0.004)	(0.010)
Age	0.001	0.002	0.001	0.010
	(0.001)	(0.002)	(0.003)	(0.009)
Years of schooling	0.007**	-0.001	0.034***	0.001
	(0.003)	(0.005)	(0.011)	(0.027)
2-digit industry	Y	Y	Y	Y
Province	Y	Y	Y	Y
R-Squared	0.113	0.131	0.094	0.159
Observations	847	868	847	868

Notes: The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in any year between 2015 and 2017. The amount of innovation subsidies in log is calculated by adding 1 to the average amount of innovation subsidies during 2015 and 2017 and then taking the logarithm. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

First, we examine the heterogeneity across firms of different sizes. We split the sample into two groups according to the total employment. Table 16 shows the results. For this table, the “small” firms are defined to be those with the number of employees smaller than the sample median. The “large” firms are those with the number of employees larger than the sample median. The table shows that the estimated coefficient on the political connection dummy is smaller and insignificant for small firms, while it is larger and significant for large firms. Whether we use the innovation subsidy dummy or the total amount of innovation subsidies as the dependent variable does not matter for the result. Compared with a large firm without political connection, a politically connected large firm is 13.0% more likely to receive any innovation subsidy (Column 2). Also, a large firm with political connections receives a 68% larger amount of innovation subsidies (Column 4). The estimated coefficient on the SOE dummy is not significantly different from zero in all specifications.

Thus, we find the correlation between political connections and receipts of innovation subsidies only for large firms. This may suggest that a firm needs to be big enough to take advantage of political connections. Exploring the reason behind this finding is beyond the scope of this paper and is left for future research.

Second, we examine whether the relation between political connection and innovation subsidies varies with corporate performances. For the measure of performance, we consider three alternatives: value-added per capita, TFP, and whether the firm reports an accounting loss. For the first two measures related to productivity, we again split the sample into two with the sample median as the threshold. For the last measure of profitability, we compare firms that have accounting losses and those that do not. Table 17 shows the result for the regressions with the innovation subsidy dummy as the dependent variable, and Table 18 shows the result when the dependent variable is the amount of innovation subsidies. Table 17 shows that the estimated coefficient on the political connection dummy is larger for firms with higher value-added per capita, with higher TFP, and without accounting losses. The point estimates suggest that politically connected firms are 10.0% more likely to receive innovation subsidies than those without political connection for firms with high value-added per capita, 13.1% more for high TFP firms, and 9.4% more for firms without losses.

When the total amount of innovation subsidies (in log) is used as the dependent variable, the results are very much the same (Table 18). The point estimates suggest that politically connected firms receive a 48% higher amount of innovation subsidies for firms with high value-added per capita, 61% higher for high TFP firms, and 40% higher for firms without losses. The results together suggest that political connection seems to be more useful in obtaining innovation subsidies when the firms have higher productivity and profitability.

Table 17. OLS regressions of innovation subsidy dummy on ownership and political connection by firm performance

	Innovation subsidy dummy					
	Value-added per capita in log		TFP in log		Have a loss	
	Low	High	Low	High	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Political connection	0.057*	0.100***	0.040	0.131***	0.045	0.094***
	(0.031)	(0.036)	(0.034)	(0.036)	(0.053)	(0.026)
SOE	-0.014	-0.053	-0.027	-0.065	0.089	-0.056
	(0.050)	(0.066)	(0.053)	(0.074)	(0.095)	(0.048)
Firm age	0.002	0.000	0.001	0.001	0.000	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Employment in log	0.030***	0.078***	0.045***	0.063***	0.017	0.062***
	(0.008)	(0.012)	(0.009)	(0.012)	(0.018)	(0.009)
Export	0.067**	-0.030	0.090**	-0.042	0.093	0.013
	(0.032)	(0.034)	(0.034)	(0.031)	(0.061)	(0.026)
Skill intensity	0.005***	0.004**	0.006***	0.005***	0.005	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Age	0.001	-0.000	0.001	0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Years of schooling	0.001	-0.001	0.002	0.001	0.003	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.003)
2-digit industry	Y	Y	Y	Y	Y	Y
Province	Y	Y	Y	Y	Y	Y
R-Squared	0.146	0.204	0.157	0.194	0.154	0.179
Observations	857	858	857	858	324	1,391

Notes: The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in any year between 2015 and 2017. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

Table 18. OLS regressions of the amount of innovation subsidies in log on ownership and political connection by firm performance

	Amount of innovation subsidies in log					
	Value-added per capita in log		TFP in log		Have a loss	
	Low	High	Low	High	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Political connection	0.140	0.480***	0.086	0.614***	0.187	0.400***
	(0.105)	(0.170)	(0.120)	(0.172)	(0.174)	(0.116)
SOE	0.159	-0.017	0.057	0.009	0.675	-0.072
	(0.243)	(0.306)	(0.250)	(0.354)	(0.415)	(0.254)
Firm age	0.003	0.005	0.001	0.006	-0.012	0.006
	(0.006)	(0.007)	(0.006)	(0.007)	(0.010)	(0.006)
Employment in log	0.177***	0.455***	0.236***	0.402***	0.151**	0.354***
	(0.037)	(0.068)	(0.044)	(0.067)	(0.067)	(0.049)
Export	0.216**	-0.122	0.327**	-0.190	0.166	0.067
	(0.108)	(0.145)	(0.126)	(0.136)	(0.201)	(0.100)
Skill intensity	0.023***	0.027***	0.024***	0.030***	0.028*	0.027***
	(0.007)	(0.008)	(0.007)	(0.009)	(0.014)	(0.007)
Age	0.002	-0.002	0.001	-0.000	0.001	0.001
	(0.005)	(0.007)	(0.005)	(0.007)	(0.008)	(0.005)
Years of schooling	0.015	-0.010	0.014	-0.004	0.009	0.001
	(0.014)	(0.020)	(0.015)	(0.021)	(0.016)	(0.015)
2-digit industry	Y	Y	Y	Y	Y	Y
Province	Y	Y	Y	Y	Y	Y
R-Squared	0.165	0.253	0.183	0.242	0.215	0.224
Observations	857	858	857	858	324	1,391

Notes: The amount of innovation subsidies in log is calculated by adding 1 to the average amount of innovation subsidies during 2015 and 2017 and then taking the logarithm. Only samples in the year 2017 are kept. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

6. Innovation Subsidy and Firm Performance

The analysis in the previous sections indicates that political connection matters more in the allocation of innovation subsidies than state ownership, and the association between political connection and innovation subsidies is especially strong for large firms and those with high productivity and profitability. In this section, we investigate the linkage of innovation subsidy and firm performance (including innovation, productivity, and profitability).

Although the information on state ownership and political connection is available only for 2017, we have three years (2015, 2016, and 2017) of observations for each firm for many other variables. This allows us to create a panel dataset and control for firm fixed effects. We also include year dummies in our regressions to control for the time-specific shocks. We again cluster the standard error at the level of the county.

First, the association between innovation subsidy and firm innovation performance is examined. We use four measures as the proxies for a firm's innovation performance and its quality: (i) the total number of patents granted, (ii) the number of patents granted in China, (iii) the number of invention patents granted in China, and (iv) the number of patents granted abroad. For each of these innovation performance measures, we have both the stock and the flow data. Table 19 presents the results using the patent stock numbers. Column 1 in Panel A reports the result of the regression with the total number of patents (in log) granted as the dependent variable. The estimated coefficient on the innovation subsidies dummy is positive and statistically significant at the 1% level. The point estimate suggests that the subsidized firms have 32% more patents than the non-subsidized firms. Column 2 regression uses the number of patents (in log) granted by the Chinese patent system as the dependent variable. The result is very similar to that of Column 1; the innovation subsidy tends to be positively correlated with Chinese patents. The estimated coefficient on the innovation subsidy dummy is smaller, presumably reflecting the fact the Chinese patents are included in the total number of patents used in Column 1 regression. A typical subsidized firm is estimated to have 29% more Chinese patents than non-subsidized firms. Column 3 examines the invention patents granted by the Chinese patent systems, which are of higher quality than other types of Chinese patents. The estimated coefficient on the innovation subsidy dummy gets smaller (0.112).

In the Column 4 specification, we look at the number of patents granted abroad, which are considered to have higher quality than domestic patents in China. In the last decade, Chinese inventors have started filing an increasing number of patents abroad. World Intellectual Property Organization (2017, p.34) points out "Filing abroad reflects the globalization of intellectual property (IP) protection and a desire to commercialize technology in foreign markets. The costs of filing abroad can be substantial, so the patents for which applicants seek international protection are likely to confer higher values." Among the patents granted abroad, those originated in China are found to have lower quality than the patents originated in other countries, though they are of a much higher quality than patents granted in China. For example, Boeing and Muller (2016) find that among PCT (Patent Cooperation Treaty) patents, those originated in China score lower than those originated in the U.S., South Korea, Germany, and Japan on the quality measure based on forward citations in International Search Reports. Squicciarini et al. (2013) find that among patents filed at the European Patent Office (EPO), patents originated in China have a lower score than the world average in terms of patent scope, family size, claims, and radicalness. The regression result in Column 4 suggests that innovation subsidies do not seem to be correlated with the high-quality patents filed abroad. The estimated coefficient on the innovation subsidy dummy is small and not significantly different from zero.

Overall, the results in Panel A of Table 19 suggest that innovation subsidies are positively associated with patenting in China, but they fail to lead to patents in foreign countries that are recognized as higher quality. Panel B of Table 19 uses the total amount of innovation subsidies (in log) instead of the innovation subsidy dummy as the main explanatory variable. The results are very much similar to those in Panel A. The Chinese innovation subsidies seem to increase mainly low-quality patents filed in China without significantly increasing high-quality patents filed abroad.

Table 20 reports the regression results using the patent flow (the number of patents granted during the year) instead of the patent stock as the dependent variable. Since we do not have a good idea about the time lags between innovation and patent granting and they may differ across industries and technology areas, we believe the regression analysis using the stock data is more reliable. Fortunately, the results are qualitatively the same in Tables 19 and 20. The innovation subsidies are associated with a larger number of low-quality patents in China but not high-quality patents abroad. The only notable difference is that the correlation between innovation subsidy and invention patents loses statistical significance when the flow data are used to count the patents.

An alternative method for alleviating the issue of time lags between innovation and patent approval is to utilize data on the number of patent applications during each year, rather than granted patents. Fortunately, the CEES dataset includes this information. We present the findings in Table 21, following Tables 19 and 20. It is evident that the results remain highly consistent.

Table 19. Fixed effects regressions of patent stock on innovation subsidy

	Total number of patents in log	Domestic patents in log	Domestic invention patents in log	Foreign patents in log
	(1)	(2)	(3)	(4)
	Panel A			
Innovation subsidy dummy	0.319***	0.294***	0.112**	0.005
	(0.062)	(0.071)	(0.054)	(0.006)
Employment in log	0.115***	0.106***	0.050***	0.001
	(0.029)	(0.029)	(0.017)	(0.003)
Skill intensity	0.003	0.002	-0.003	-0.000
	(0.003)	(0.003)	(0.003)	(0.001)
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
R-Squared	0.972	0.970	0.967	0.973
Observations	5,267	5,267	5,267	5,267
	Panel B			
Amount of innovation subsidies in log	0.082***	0.072***	0.033**	0.003
	(0.016)	(0.019)	(0.015)	(0.002)
Employment in log	0.111***	0.104***	0.047***	0.000
	(0.028)	(0.028)	(0.017)	(0.003)
Skill intensity	0.003	0.002	-0.003	-0.000
	(0.003)	(0.003)	(0.003)	(0.001)
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
R-Squared	0.972	0.970	0.967	0.973
Observations	5,267	5,267	5,267	5,267

Notes: The dependent variables are calculated by taking the logarithm after adding 1. The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in each year. The amount of innovation subsidies in log is calculated by taking the logarithm of the amount of innovation subsidies obtained by the firm in each year after adding 1. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

Table 20. Fixed effects regressions of patent flow (newly granted patents) on innovation subsidy

	Total number of patents in log	Domestic patents in log	Domestic invention patents in log	Foreign patents in log
	(1)	(2)	(3)	(4)
	Panel A			
Innovation subsidy dummy	0.215***	0.202***	0.051	-0.001
	(0.078)	(0.076)	(0.057)	(0.001)
Employment in log	0.089**	0.088**	0.061***	0.000
	(0.039)	(0.038)	(0.022)	(0.004)
Skill intensity	-0.005	-0.005	-0.002	0.001
	(0.005)	(0.005)	(0.004)	(0.001)
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
R-Squared	0.855	0.850	0.822	0.849
Observations	5,267	5,267	5,267	5,267
	Panel B			
Amount of innovation subsidies in log	0.051***	0.046**	0.014	0.001
	(0.019)	(0.019)	(0.014)	(0.001)
Employment in log	0.088**	0.087**	0.060***	-0.000
	(0.039)	(0.038)	(0.021)	(0.004)
Skill intensity	-0.005	-0.005	-0.002	0.001
	(0.005)	(0.005)	(0.004)	(0.001)
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
R-Squared	0.855	0.850	0.822	0.849
Observations	5,267	5,267	5,267	5,267

Notes: The dependent variables are calculated by taking the logarithm after adding 1. The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in each year. The amount of innovation subsidies in log is calculated by taking the logarithm of the amount of innovation subsidies obtained by the firm in each year after adding 1. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

Table 21. Fixed effects regressions of patent applications on innovation subsidy

	Total number of patents in log	Domestic patents in log	Domestic invention patents in log	Foreign patents in log
	(1)	(2)	(3)	(4)
		Panel A		
Innovation subsidy dummy	0.274***	0.276***	0.061	-0.004
	(0.074)	(0.074)	(0.049)	(0.003)
Employment in log	0.102***	0.099***	0.083***	-0.004
	(0.038)	(0.036)	(0.028)	(0.005)
Skill intensity	0.001	0.001	0.002	-0.000
	(0.005)	(0.005)	(0.003)	(0.001)
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
R-Squared	0.873	0.871	0.867	0.888
Observations	5,267	5,267	5,267	5,267
		Panel B		
Amount of innovation subsidies in log	0.077***	0.078***	0.025**	0.001
	(0.018)	(0.018)	(0.012)	(0.001)
Employment in log	0.097***	0.094***	0.080***	-0.004
	(0.037)	(0.035)	(0.027)	(0.005)
Skill intensity	0.001	0.001	0.002	-0.000
	(0.005)	(0.005)	(0.003)	(0.001)
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
R-Squared	0.874	0.872	0.867	0.888
Observations	5,267	5,267	5,267	5,267

Notes: The dependent variables are calculated by taking the logarithm after adding 1. The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in each year. The amount of innovation subsidies in log is calculated by taking the logarithm of the amount of innovation subsidies obtained by the firm in each year after adding 1. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

Table 22. Fixed effects regressions of productivity and profitability on innovation subsidy

	Value-added per capita in log	TFP in log	Have a loss
	(1)	(2)	(3)
		Panel A	
Innovation subsidy dummy	-0.014	-0.044	-0.033
	(0.053)	(0.064)	(0.030)
Employment in log	-0.075	0.205**	-0.059**
	(0.093)	(0.102)	(0.024)
Skill intensity	-0.024*	-0.019	0.003
	(0.014)	(0.013)	(0.003)
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
R-Squared	0.931	0.939	0.726
Observations	5,267	5,267	5,267
		Panel B	
Amount of innovation subsidies in log	-0.003	-0.010	-0.008
	(0.013)	(0.016)	(0.007)
Employment in log	-0.076	0.206**	-0.059**
	(0.093)	(0.102)	(0.025)
Skill intensity	-0.024*	-0.019	0.003
	(0.014)	(0.013)	(0.003)
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
R-Squared	0.931	0.939	0.726
Observations	5,267	5,267	5,267

Notes: Value-added per capita is the logarithm of the value-added divided by the number of employments. The innovation subsidy dummy indicates whether the firm obtained innovation subsidies in each year. The amount of innovation subsidies in log is calculated by taking the logarithm of the amount of innovation subsidies obtained by the firm in each year after adding 1. *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors are clustered at the county level.

We also examine the association between innovation subsidy and firm productivity and profitability. Table 22 shows the results from regression analyses with value-added per capita (in log), TFP (in log), and the loss dummy as dependent variables. Panel A reports the results for specifications using the innovation subsidy dummy, and Panel B reports the specifications using the total amount of innovation subsidies (in log) as the explanatory variable of interest. In both panels, the results are qualitatively the same; the estimated coefficient on the innovation subsidy variable is not significantly different from zero. Thus, the innovation subsidies in China do not seem to make the recipient firms more productive or profitable. Although the subsidies appear to boost patent applications in the Chinese patent office, they do not contribute to enhancing firm performance.

In summary, we find that the total number of patents granted indeed increases with innovation subsidies. The number of patents granted abroad that have higher quality, however, does not increase significantly with the innovation subsidies. These results suggest that the innovation subsidies may be encouraging only incremental technological improvement and do not seem to generate truly innovative patents that are granted in foreign countries with stronger patent systems. Our result is consistent with the findings by Dang and Motohashi (2015), which examined the patent data in China. They find that the subsidy programs that they examine actually encourage firms to narrow the scope of patents to make it easier to obtain patents. Also, it seems that the innovation subsidies fail to improve the bottom-line performance of the recipient companies. This suggests that the patents that are encouraged by the subsidies do not add much to productivity or profitability.

7. Conclusion

In this paper, we examine two distinct characteristics of Chinese corporate governance, namely still strong state ownership and political connection of private firms, and how those influence the allocation of innovation subsidies. We make four important findings. First, the innovation subsidies are allocated preferentially to politically connected firms. Because politically connected firms are not necessarily more innovative firms, the result suggests inefficiency of the allocation of innovation subsidies. Second, we find political connection is a more important determinant of allocation of the innovation subsidies than state ownership. When we include both political connection and state ownership in our regression models, the coefficient estimate on the state ownership becomes statistically insignificant. Third, firms that receive subsidies file more patents but do not necessarily file more patents outside China. Since the quality of patents granted in China is lower than those in foreign jurisdictions, the result suggests that innovation subsidies often encourage firms to come up with incremental changes and not truly innovative technologies. Fourth, the firms that receive innovation subsidies do not show higher productivity or profitability. Thus, the innovation subsidies do not seem to help the bottom lines of the recipient firms.

Overall, our findings suggest that the allocation of innovation subsidies is inefficient, that the subsidies encourage only incremental innovations and not radical ones, and that the subsidies do not help the bottom lines. These make one doubt the effectiveness of China’s innovation policy so far.

Declaration of Competing Interests

The authors declare that they have no other relevant or material financial interests that relate to the research described in this paper.

Data Availability

The authors do not have permission to share data.

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