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State Ownership and Corporate Innovation Efficiency

Abstract

The conventional wisdom is that state ownership may hinder patenting through reduced incentives and pronounced agency problems associated with state-owned enterprises (SOEs). Empirical evidence from a variety of contexts, including the U.S., Europe, and China, is consistent with this view, including evidence that shows that reductions in state ownership are associated with an increase in patent counts. In this paper, we investigate the innovative efficiency of Chinese SOEs. Innovative efficiency refers to patents/R&D expenditure, and not patent counts. The data indicate that SOEs, and especially central government SOEs, are substantially more innovatively efficient than non-SOEs. The relative innovative efficiency of SOEs is more pronounced amongst firms with high financial constraints, those removed from financial centers, and those in high-technology industries. The data are consistent with the view that in the Chinese context, there are favorable benefits to state ownership through access to talent, connections, and technological resources that enables a sustained commitment to R&D to enable efficient patent outcomes relative to R&D expenditure.

Keywords: State ownership, Innovative efficiency, Financial constraints

JEL Codes: G32, G38, O31, O38

"China Pushes For Innovation In State-Owned Enterprises, But Is Change Possible?"

- Forbes, August 22, 2016[1]

"China's desire to improve the efficiency of its state-owned enterprises is real, just don't expect the reform process to follow a western model."

- Bloomberg September 8, 2016[2]

1. Introduction

State ownership is typically associated with less innovative efficiency. The 1980 Bayh–Dole Act in the U.S. was introduced to transfer ownership of innovation from government to private parties (Eisenberg, 1996). There is much evidence from the U.S. and Europe that state ownership is a 'dead hand' with inefficient bureaucratic structures and reduced incentives to innovate (Eisenberg, 1996; Shleifer, 1998; Verspagen, 2006).

China has recently become one of the world's largest economies (Allen et al., 2005) and the world's leading generator of patents in the world (Ang et al., 2016). As China's economy is dominated by state-owned enterprises (SOEs), there is significant attentionamongst practitioners and academics alike as to whether or not these SOEs are innovatively efficient. Consistent with the government is a 'dead hand' perspective; evidence from China shows that partial transitions from state to private ownership in the 1990s (Jefferson et al., 2003) and 2000s (Tan et al. 2015) were associated with an increase in patent counts.

1 http://www.forbes.com/sites/sarahsu/2016/08/22/china-innovation-state-owned-enterprises/#62b2e9695110

2 http://www.bloomberg.com/news/articles/2016-09-08/goldman-sachs-sees-chinese-soe-reform-just-not-as-west-knows-it

In this paper, we revisit this general question of whether or not SOEs are good or bad for innovation by making use of data that not only count patents but also account for R&D expenditure. We use the "innovation efficiency" measure of Hirshleifer, Hsu, and Li (2013) and Cohen, Diether, and Malloy (2013) to examine whether or not SOEs in China possess more innovative efficiency. Prior research on patents in China (e.g., Jefferson et al., 2003; Choi et al., 2011; Tan et al., 2015) used samples where patents could not be matched to R&D expenditures. In this paper, we find differential evidence on the efficiency of SOEs for innovation. In particular, unlike prior work that suggests SOEs produce less innovation, we find that SOEs are more innovatively efficient than their non-SOE counterparts.

In baseline regression results, we find a significantly positive association between SOEs and innovative efficiency. By using the Heckman MLE selection model, we rule out the potential selection bias due to the difference in size and age between SOEs and non-SOEs. Our further cross sectional tests are conducted to consider the differences in the impact of SOEs on innovative efficiency in subsamples partitioned according to standard proxies for financial constraints, including the WW index (Whited and Wu, 2006), the KZ Index (Lamont, Polk and Saa-Requejo, 2001), and firm size (market capitalization, Livdan, Sapriza, and Zhang, 2009). The data indicate that SOEs are even more innovatively efficient when compared to non-SOEs among firms with pronounced financial constraints.

We run further subsample tests according to the location of the firms' headquarters, which proxy for the difficulties of the firms' financing. We define firms with headquarters in Shanghai, Beijing, and Shenzhen as one group, with relatively easier access to finance,comparingthe rest of the firms as "other."[3] For those firms that with

[3] These cities ranked as the top 3 cities with the best financing environment in "Top 20 Cities with Best

headquarters not located in the top financial centers, the SOEs' efficiency of innovative production is found to be significantly higher than the non SOEs'. This result suggests that for firms with more difficulties in accessingfinancing, SOEs are more innovatively efficient. For robustness, we also partition the sample into coastal areas and "other," defined as whether their headquarters are located in the coastal provinces of China (15 of the "Top 20 Cities with Best Financial Environment in China" come from the coastal provinces).[4] We also employ the market index constructed by Fan et al. (2010) to compare the relatively developed area with more institutional environmentwith other developing provinces in China. Similar results hold.

Also, we consider regressions to test the innovative efficiency of SOE versus non-SOE firms under different market characteristics. Competitive product markets are a good external monitor for improving a firms' governance and increase managerial efforts (Schmidt, 1997; Bos, Economidou, and Sanders, 2013). Similarly, the high-technology industry is competitive, and agency problem are often less than in other industries. We use product market competition levels and a high-technology industry dummy, respectively, and make them interact with the SOE dummy. The data indicate that the SOEs in more competitive markets and operating in high-tech industries tend to be moreinnovatively efficient than non-SOEs.

Through what channel are SOEs more innovatively efficient in China? An important benefit of SOEs is the stable access to talent, financial resources, connections, and technological resources that enable a sustained commitment to R&D

Financing Environment in China," from China Venture Capital and Entrepreneurship Research Center.

[4] According to the report, "Top 20 Cities with Best Financing Environment in China" from China Venture Capital and Entrepreneurship Research Center, the top 20 cities, in order, are Beijing, Shenzhen, Shanghai, Suzhou, Hangzhou, Guangzhou, Wuhan, Nanjing, Tianjing, Chengdu, Changsha, Shaoxin, Chongqing, Dongguan, Jinan, Changzhou, Ningbo, Xian, Fuzhou, and Xiamen.

to enable patent outcomes (Cumming, Rui, and Wu, 2016). China's state sectors are the most important force in financing and carrying out research to spur innovations. SOEs in China are the most important innovators. For example, the newly-announced Nobel Prize winner Youyou Tu has proved to the world that the state sector can perform well in top innovative research. Ms. Tu's invention of anovel therapy for anti-malaria (which kills 200 million people each year) could not have been achieved inthree years without the Chinese government's backing and involvement, not only in terms of funding but also in political support, the provision of research teams, and sample collections. Moreover, in China, mostuniversities belong to and are owned by the local government; several top schools, such as Peking University and Tsinghua University, are directly owned by the central government. Thus, it is much easier for the SOEs to cooperate with these universities for their top level research, and even work together with their super talents, with whom private firms usually have very few opportunities to meet. To this end, we also run tests by dividing SOEs into central SOEs and local SOEs, according to whether their ownership belongs to the central or local government. The data indicate that central SOEs have a more pronounced impact on innovative efficiency than local SOEs.

Our paper contributes to the innovative efficiency and state ownership literature. We show for the first time in the literature that SOEs are more efficient than non-SOEs in China, counter to prior evidence that examines patent counts in China without accounting for R&D expenses (Tan et al., 2015). Furthermore, we show that the superior innovative efficiency of SOEs is more pronounced among firms with higher financial constraints and those in more competitive product markets. In general, our paper highlights the importance of ownership and institutional features that jointly shape a corporation'sinnovative efficiency in an emerging market.

This paper continues as follows: Section 2 discusses the additional background and literature review; Section 3 explains the data andinnovative efficiency measures; Section 4 demonstrates the empirical results of the main findings;Section 5 provides concluding remarks and suggestions for future research.

2. Literature Review and Hypotheses

Since 2005, China's SOEs have been partially privatized SOEs. China's privatization is different from typical privatization practices around the world (Lipton et al., 1990; Boycko et al., 1994; Biais and Perotti, 2002). China adopted a partial privatization program in 2005 through which only a small percentage of shares float in the equity market. That is, although a great number of China's SOEs have been listed on the stock market, few are entirely privatized. The Chinese partial privatization program means that the government remains the largest shareholder. There are two main privatization waves in China: the Share Issue Privatization (SIP) and Split-Share Structure Reform (SSSR) (2005). SIP was launched in the early 1990s, when the Chinese government finished the establishment of two stock exchanges, the Shanghai and the Shenzhen Stock Exchange. The Chinese government managed to have a portion of the shared SOEs' to be listed on these two exchanges to be traded on the public market. Although a great proportion of shares were still non-publicly tradable during this privatization program; it was considered huge progress to the privatization process that switched the button from zero to one. Thus, all the publicly-traded SOE shares can be considered as partially-privatized. China's privatization approach is, therefore, gradual. The reform in China has progressed; the government dictates the reform with the aim to gradually introduce a significant but minor percentage of public minority ownership traded in the stock market. Such partial privatization allows the Chinese government to retain a substantial portion of the ownership of partially-privatized SOEs, especially medium and large firms. In doing so, China adopted a strategy of “keeping the larger ones and letting go of the smaller ones.” Sun and Tong (2003) show that the share issue privatization (SIP), which is the first wave of privatization in China, is effective in improving an SOE’s earning ability, real sales, and worker productivity. Using China's secondary wave of privatization, Split-Share Structure Reform, Liao, Liu and Wang (2014) demonstrate that further privatization quickly boosted an SOE’s output, profits, and employment. Also, the reform improved corporate governance and share price informativeness (Hou et al., 2012; Hou and Lee, 2014).

The effect of privatization on corporate efficiency has been a central topic in the literature which has largely suggested efficiency improves after privatization. Most governments around the world, especially in developing countries, retain significant ownership of SOEs after they are listed through share-issue (so called “partial privatization”). For example, in a survey from 59 countries regarding their share issue privatization process, Jones et al. (1999) found that there are only 11.5% firms that had sold out all of their ownership to the public, and less than 30% of firms chose to sell more than half of their shares in the IPO. The supporters of partial privatization argue that the government should keep SOEs since they can play an important role in key industries, such as energy and transportation, and fulfill the government’s innovation policies. It is widely believed that SOEs lack efficiency (Megginson, Nash and Randenborgh, 1994). Empirical evidence shows that partial privatization improves firm performance and has casual effects on corporate efficiency. Supporting this view, Megginson and Netter (2001) document that the post-privatization performance of most firms is better than pre-privatization performance. Dewenter and Malatesta (2001) and Claessens and Djankov (2002) found that newly privatized SOEs' performance improves.

A study by Tan, et al. (2015) shows that privatization of SOEs in China has a positive causal effect on firm innovation output. However, the challenge of measuring a firm's innovation ability remains. Hall and Ziedonis (2001) argue that patents do not reflect productivity, because large corporations can invest more resources, such as research and development, and file larger numbers of patents than small firms. It is therefore still not clear from prior research whether SOEs are more efficient in converting investment or R&D expenses into innovative output. This is particularly important to determine, as it is well known that innovative investment has its own, unique features, such as high uncertainty, intangibility, and severe information asymmetry (Kumar and Langberg 2009; Hall and Lerner 2010). Innovation investment in SOEs is often plagued by agency problems, which means that SOEs' innovative efficiency should be much worse than privately-owned enterprises.

We thus rely on the measurement developed by Hirshleifer, Hsu, and Li (2013) to examine the performance of investment on innovation. They propose the measurement of innovative efficiency—defined as the number of successful patent applications produced per unit of research expense—to better capture patent performance or the efficiency of transforming expenses into innovation outcomes. Cohen, Diether, and Malloy (2013) show this measure captures well the efficiency of converting R&D expenses into innovative outputs such as patents. We aim to answer the important question of whether SOEs are efficient after being partially privatized, compared to privately-owned enterprises withregard to their innovative investment and research expenditures.

There is scant literature regarding the SOEs' efficiency in investment on innovation. The Chinese government, like all other countries' governments, is increasingly promoting, encouraging, and investing in innovation through SOEs mainly, as the nation realizes that technological innovation is vital to a country's competitive advantage (Porter, 1992) and economic growth (Solow, 1957; Baumol, 2001). Governments commit a large number of funds to subsidize or incentivize corporate innovation of both SOEs and non-SOEs. SOEs, however, are often favored to receive such investment or grants from the government.

On one hand, SOEs, compared to private owned firms, are more susceptible to agency problems due to lack of effective monitoring and incentives (Shleifer, 1998), and hence be less innovative efficient. Incentives of efficiently investing in innovation may be jeopardized by such agency issues. Several additional channels of SOEs' negative influence on efficiency exist, according to previous literature. Sappington and Stiglits (1987) find there is a lower transaction cost for the government to intervene in SOEs than private firms. More importantly, many papers point out that the "soft" budget constraints caused by states' unwillingness to let SOEs go bankrupt would lower the stimulating effect of financial constraints (Berglof and Roland 1998, Hessel and Rapaczynski 2000). Hansmann and Kraakmann (2000) suggest that governments may have other objectives for SOEs than profit or efficiency maximization. All these reasons would also impede innovative investment efficiency in the same way they hinder the operating efficiency. The inefficiency phenomenon is comprehensively summarized by Megginson and Netter (2001) and Megginson (2010).

On the other hand, there are arguments supporting the innovative efficiency of SOEs. Gupta (2005) argues that the stock market can monitor and provide incentives to a management team of SOEs.Gupta (2005) argues that the stock market can monitor and provide incentives to a management team of SOEs. He finds that partial privatization has a positive impact on a firm's profitability, productivity, investment, and efficiency. Almeida, Hsu, and Li (2013) show that financial constraints may contribute to a firm's efficiency of innovative activities by mitigating free cash flow problems,in which firms make unproductive R&D investments in fields out of their direct expertise. Thus, financial constraints, (e.g., lack of free cash flow and a mandated payment of dividend) all serve to reduce agency problems. SOEs with such features are as efficient as non-SOEs in innovation. Furthermore, external monitoring mechanisms also exist, such as product and technology market competition. SOEs operating in a high-tech sector or those facing intense product market competitionmay be as innovation efficient as non-SOEs..Megginson et al. (1994) also point out that partially private ownership allows for internalizing the benefits of performance improvements and that publicly-listed shares allow these benefits to be capitalized into the price of the firm's stock. These papers suggest that partial privatization leads to efficiency in SOEs.

The Global Innovation Index (GII) conducted by Cornell University, the INSEAD Business School, and the World Intellectual Property Organization (WIPO) treats innovative efficiency as one of the most important components for innovation and economic development. High-ranking nations include not only developed countries with highly-privatized markets but also those countries that preserve a large portion of state-controlled enterprises and are newly partially privatized, such as Singapore and China. However, this innovative ranking of countries on the GII index, such as China, is somehow contradicted with the previous literature of SOEs' low efficiency. Hence, it is important to scrutinize the efficiency of SOEs regarding innovation, compared to non-SOEs, since the government has the alternative of financing innovation through non-SOEs. In view of the gap in the prior literature, and arguments both for and against the innovative efficiency of partially privatized SOEs, we examine for the first time below whether or not SOEs are more innovation efficient than their non-SOE counterparts in China.

3. Data and Measurements

There are 25,098 firm-year observations existing in the sample, including 11,589 SOEs and 13,486 non-SOEs, from 1998to 2015. We exclude the financial and utility firms since they share different disclosure regulations, and their liquidity positions are different from the other firms. We also dropped and/or delisted firms, such as ST or *ST, because they are under stricter regulations and trading requirements. We set the starting point as 2009, because, in 2007, Chinese firms adopted a new, unified set of accounting standards and principles, which requires firms to disclose R&D expense data.[5] Since the calculation of innovative efficiency needs at least a firm'sprevious 3-year average R&D Expense, our sample starts from 2009.

Considering the impact of extreme values and outliers, we winsorize all firm characteristics at the 1st and 99th percentiles. To balance the sample and keep the same firms in each year, we require all the firms to have existedon the Shanghai or the Shenzhen Stock Exchange for more than three years. Tan et al. (2015) point out that the firm ownership type (SOEs vs. non-SOEs) is an important determinant of firm innovation;therefore, we manually combined the firm ownership data from the CSMAR, the China Centre for Economic Research (CCER) Database, and the Wind

[5] New Accounting Standards for Enterprises No.6 (Intangible Assets) required firms to identify, quantify, and disclose their R&D expense as an independent item. These standards became effective on Jan 1st 2008.

Database, as well as the official website of listed companies. All the patent data was hand-collected before 2014 from the State Intellectual Property Office of China (SIPO), which is directly affiliated with the China State Council and is responsible for registering intellectual property, including patents.Sincea truncation problem existed from SIPO, we also useddatabases fromtheChina Stock Market &the Accounting Research Database (CSMAR), as they disclosepatent numbers at the end of each year. Otherfinancial variableswere obtained from CSMAR.

3.1 Innovation Efficiency Measurements

According to the Patent Law of the People's Republic of China, three types of patents are defined and filed with SIPO: invention patents (Type I), utility model patents (Type II), and appearance design patents (Type III). The invention patents (Type I) include new technical solutions to products, methodologies, or the improvement of producing a process, which is the most innovative type of patent and is similar to a U.S. utility patent. Type II patents include new technical ideas for a product's shape and structure and aim for practical use, which does not reach the requirement for being as highly innovative as invention patents. The appearance design patents (Type III) include new designs for a product's shape, pattern, and colorfulness, for the improvement of aesthetics, and an adaptation for industrial application. We obtained the information about the patent application date, application ID, publication ID, granting date, and patent ID, along with the names of inventors and applicants, in the SIPO database as well as in the patent database from CSMAR.

In order to test how efficiently a firm transforms innovative input (R&D Expense) into innovative output (Patents), we follow Hirshleifer, Hsu, and Li (2013) to construct a measurement of innovative efficiency, which is calculated as the number of ultimately successful patent applications filed by firm i in year t ($NumPat_{i,t}$) divided by firm i's weighted cumulative R&D investment from year $t-2$ to year t:

$$NumPat_{i,t} / (XRD_{i,t} + 2/3^{*} XRD_{i,t-1} + 1/3^{*} XRD_{i,t-2}), \quad (1)$$

where $XRD_{i,t}$ indicates firm i's R&D investment in year t. We only use the number of invention patents (Type I) as our main counts for the patent number ($NumPat_{i,t}$), because neither appearance design patents (Type III) nor practically new patents (Type II) has the same level of importance as the invention patents. The expenditure amount of the R&D investment for Type IIand Type III is obviously much lower than that for Type I, as well.

For example, one of Tsingtao beer's Type 1 patent applications is named as "A biology method of systematically detecting contaminated bacteria," which needs around three years of timeto be implement, millions of dollars of investment, and an entire laboratory of research teams. In contrast, Type IIand Type III patents usually include projects like, "An invention of the package plate of glass bottle," and "A new design pattern for the stickers of beer bottles."

Although these Type II and Type III patents are still essential to a firm's marketing activities, the research expenditure on them is apparently much lower than that of the Type I patents. Therefore, merely keeping the Type I patents as the measurement setting can accurately and directly illustrate how efficiently firms transform their innovative input into real and essential innovative output. For robustness, we also consider alternative measures of innovative efficiency by including the other types of patents and setting different sample periods of R&D Expense. The results are similar, but the measurementsusing Type II or Type III patents have less magnitude and significance. These results are available upon request.

One limitation and concern is the short sample period, due to the R&D expense data availability, from 2009. For a robustness check, we substitute the R&D expense withintangible assets to construct the innovative efficiency measure by using the same calculation and find robust evidence. These results are also available upon request.

Figure I plots the trend for the number of patents, the R&D expense, as well as the innovation efficiency measurement. There is a very clear increasing pattern for both patent number and R&D expense, indicating the importance and awareness of innovation in China. The number of patents from SIPO droppedsignificantly in 2014, suggesting a potential truncation issue.As for efficiency measurements, SOEs have generally higher innovative efficiency than non-SOEs in most years, although the gap is much closer in the most recent period. We also show that the number of patents divided by the XRD(lagged R&D expense) and the pattern is still similar.

3.2 Data of SOEs and financial controls

By following the existing literature (L. Liao et al. 2014 and M. Firth et al. 2010), we identify the ultimate controlled shareholder by tracing back the control chains of listed firmsby using the ownership structurefrom CSMAR. We further supplement the ownership data with WIND, CCER, and hand-collected data fromfirms' annual reports for cases in which the ownership information is missing or incomplete from CSMAR.

To be classified as an SOE, a listed company has to be ultimately controlled by a government entity,meaningacentral government, a local government, and/or other government agency, such as the State-Owned Assets Supervision and Administration Commission (SASAC). Otherwise, we consider an SOE as a privately-controlled firm, such as a village or foreign company. We then identify the SOE Dummyto be equal to 1, if a firm is an SOE in year *t*, and zero otherwise.

In the multivariate analysis, we control for an array of firm and industry-level characteristics that might affect a firm's innovative efficiency according to the literature. Hall and Ziedonis (2001), for example, argue that the number of patent applications and the number of patent citations are positively related to firm size. For this reason, we control for the firm size, measured by the natural logarithm of total assets Ln (Assets). We also control forresearch and development expenses, divided by total firm assets, since R&D expenses play an essential role in financing firm innovation (Atanassov, 2013). Additionally, the following variables are considered: firm age, measured by years elapsed since the firm was first listed (Firm Age); profitability, measured by return on assets (ROA); growth opportunities, measured by Tobin’s Q (Tobin’s Q); the ratio of cash flow to total firm assets(Cash Flow); the debt-to-assets ratio (Leverage); the rate of investment in fixed assets, measured by capital expenditures divided by total firm assets(CAPEX); the ratio of tangible assets divided by firm assets(Tangible); and product market competition, measured by the Herfindahl index of the level-2 industry code provided by the China Security Regulation Commission (CSRC), based on sales (Herfindahl Index). Table 1 provides a more detailed definition or calculation of the variables above.

3.3 Summary Statistics

Table 2 summarizes the innovative efficiency and firm characteristics for SOE and private firms.In Panel A, the number of Type I patents from SIPO is higher than that from the CSMAR measurement, similar to the innovation efficiency measurement. Specifically,on average, SOEs have a mean of 0.1595 (SIPOdata; and .2164 with CSMAR data) of their efficiency for producing innovation, which means every one million CNY (around 160,000 USD) input of research and development expenses would produce 0.1595 invention patent (Type I), while the average number of non-SOEs is 0.1001 (SIPO data; and 0.1836 CSMAR data). The mean difference of innovative efficiency between SOEs and non-SOEs is both economically and statistically significant. That is, on average, the SOEs are more efficient in producing innovation than the non-SOEs. This, however, may be caused by the size and age effect, since SOEs tend to be larger and older than private firms; there are other plausible reasons; e.g., SOEs hold less cash and possess a higher leverage ratio.

[INSERT TABLES 1-2 AND FIGURE 1 ABOUT HERE]

In additional unreported univariate tests, we compare the mean and medians of innovative efficiency for SOEs and non-SOEs according to the firm's level of financial constraints measured by a KZ Index (Kaplan and Zingales, Lamont, Polk, and Saa-Requejo, 2001). Firms with a KZ Index above the 50th percentile are considered to be financially constrained, and, otherwise, financially unconstrained.[6] The univariate tests indicate that financially constrained SOEs have more efficiency in innovation than the private firms with financial constraints. Similarly, financially unconstrained SOE are less efficient in innovation than the financially unconstrained private firms. Those additional univariate results are available upon request. We provide multivariate evidence below.

4. Empirical Tests

4.1 Baseline regressions

[6]Same univariate tests are also conducted by using other measures as the proxy of financial constraint, such as the WW Index and the dividend payment status of firms, which produced similar results.

Table 3 reports the baseline multivariate regression results of the association between state ownership and the innovative efficiency during the post-privatization period. We use the panel regression controlled for both year and industry fixed effects to avoid unobserved year and industry invariant specific factors. The main independent variable is SOE Dummy, which equals one, if the firm's ultimate controlling ownership belongs to the state/local government throughout the sample period, and zero otherwise. All regressions are controlled for the natural logarithm of total assets, the firm age, the return on assets, Tobin's Q, cash flow, the leverage ratio, the R&D expense, capital expenditure (CAPEX) and tangible assets, the high technology dummy, market competition, and the industry SOE structure.

[INSERT TABLE 3 ABOUT HERE]

As Table 3 shows, the estimated coefficient of the SOE signal is positive and significant. The number of patents invented by spending per million (CNY) R&D input of SOEs is 0.036 higher than the one of private firms (Column 1 for SIPO data). Given that the firms have an innovative efficiency average of 0.1244(Table 2), this means that SOEs are 28.9% more innovatively efficient than non-SOEs. Column (2) for CSMAR data indicates even greater economic significance with 0.055/0.1970=27.9% greater innovative efficiency amongst SOEs than non-SOEs. The economic significance is more pronounced with propensity score matching in columns (3) and (4) for firm size and industry, while the Heckman regressions in columns (5) and (6) show slightly reduced economic significance. The greater innovative efficiency of SOEs is significant at the 1% level in each of the 6 models in Table 3.

4.2 Robustness checks

[INSERT TABLES 4 AND 5 ABOUT HERE]

Table 4 presents the regression results similar to those in Table 3. The focus of Table 4 are interaction terms, such as SOE*KZ, SOE*WW, and SOE* Div Dummy, which all capture the variation between SOEs and non-SOEs regarding innovative efficiency when a firm's level of financial constraint varies. Firms suffering from high financial constraints usually have a high KZ index, a high WW Index, and no dividends. The regression results show that the coefficients of SOE*KZ and SOE*WW are positive (as expected), and the coefficient of SOE*Div Dummy is negative[7] (although dividends are an imperfect signal of financial constraints). All the coefficients of interaction terms are statistically and economically significant. This finding supports our hypothesis that SOEs with morefinancial constraints are even more innovatively efficient than non-SOEs.

Similar findings are shown in Table 5, where we segregate the sample by financially constrained and non-constrained firms, where the data clearly indicate that SOEs are substantially more innovatively efficient for financially constrained firms. The data in columns (1) and (2) indicate that SOEs are 46.4% more innovatively efficient for the subset of financially constrained firms as measured by the KZ index (while there is no difference between SOEs and non-SOEs for unconstrained firms). Columns (3) and (4) show that SOEs are 33.2% more innovatively efficient for the subset of financially constrained firms as measured by the WW index (and, as with the KZ index, there is no difference between SOEs and non-SOEs for unconstrained

[7]The negative interation of a Dividend Dummy with anSOE Dummy indicates that SOEs with non-dividend payment are efficient in innovation, consistent with the measurement of a financially constrained index.

firms under the WW index). Also, the data indicate in Table 4,Columns (5) and (6) that SOEs are 25.1% more innovatively efficient among the subset of non-dividend paying firms, and 21.9% more innovatively efficient among the subset of dividend paying firms.

[INSERT TABLE 6 ABOUT HERE]

Table 6 presents the OLS regression results for the difference of innovative efficiency between SOEs and non-SOEs when dividing firms into two subsamples according to their headquarter location and by market conditions. In Column (1) and (2), subsamples are divided according to whether the headquarter location is in Beijing/Shanghai/Shenzhen or other cities, while Column (3) and (4) are divided by whether the headquarter location is along the coastal area or not. This is to test whether firms based in locations with poorer financing environments have differential innovative efficiency. Column (5) and Column (6) are divided by whether firms are located in the Special Economic Zone or not. and Column (7) and Column (8) identify the market development situation according to the local market index higher(lower) than the median of the market index by each year from Fan and Wang (2012).

The research results in Columns (2),(4), (6), and (8) display the difference in innovative efficiency between SOE and non-SOEs and are statistically significant. The magnitudes of coefficients are economically large for SOEs in the poorer financing environments as well as in a more domestic,institutional setting.Coefficients in Columns (2), (4), (6), and (8) being 0.050, 0.048, 0.037, and 0.041, respectively, means SOEs are 31.3%, 30.1%,23.2%, and 25.7%, respectively, more efficient in producing innovation than non-SOEs. Furthermore, the results in Column (1), (3),(5), and (7) show that there is no significant innovation efficiency difference between SOEs and non-SOEs in districts with a good financing environment.

[INSERT TABLE 7 ABOUT HERE]

Table 7 provides the results of the subsample test depending, on product market competition. We proxy the product market competition by using the Herfindahl Index (H-index) and group the firms according to the median of H-index. Firms with the H-index above median are considered to be in low competitive markets and vice versa. This is to test how the difference between SOEs and non-SOEs in innovative efficiency would vary in a product market with different levels of competition. For robustness, we also test the interaction term SOE*Hindex, which captures the similar relationship between the SOES and innovative efficiency, according to the differential market competition.

The results in Columns (1) and (2) for the different industry groups in Table 6 demonstrate that the SOEs produce innovation with significantly more efficiency in both high and low competitive markets, although the economic significance is slightly greater in low competitive markets. When we consider the full sample and the interaction of SOE*Hindex, the effect is positive and economically significant for LV3 and LV4 industries, suggesting SOEs are more innovatively efficient for more competitive industries.

[INSERT TABLE 8 ABOUT HERE]

Table 8 shows the results of similar regressions as Table 7 by dividing firms into high-technology industries and the rest. We adopt Hall and Lerner's (2010) taxonomy, where the high-technology sector comprises pharmaceuticals, office and computing equipment, communications equipment, and electronic components. This is to test whether or not the difference between SOEs and non-SOEs varies when firms belong to high-technology industries. For robustness, we also test the interaction term of

SOE*Hi-Tech, which capturesa similar relationship between the SOEs and innovative efficiency, according to the high-tech industries or not. The results in Columns (1), (2), and (3) demonstrate that the SOEs are significantly more innovatively efficient in high-technology industries than in non-high-technology industries, and the coefficient of SOE Signal and SOE*Hi-Tech is economically significant and large. For example, the coefficients of SOE Signal in Column (1) indicate that SOEs in high-technology industries are 32.0% (= 0.051 / 0.1595, when compared with the average efficiency of private firms) significantly more efficient in producing innovation than private firms. While for the firms in non-high-technology industries, there is no such significant relationship. In addition, the coefficient of SOE*Hi-Tech in Column (3) implies that SOEs are with more innovative efficiency in high-technology industries by 32.0%, in comparison with average firms.

Overall, the results in Tables 7 and 8 provide compelling evidence from the industry aspect to support the argument that SOEs are more innovatively efficient, even in industries with high market competition and high technology. An interpretation is that the synergy of monitoring from both state and private shareholders with SOEs and competitive external markets enable SOEs to make optimal investment decisions and to be more creative in improving capital efficiency. Moreover, SOEs have better and more stable access to resources and talent that enables more efficient use of innovation expenditures.

[INSERT TABLE 9 ABOUT HERE]

In order to prove this priority of SOEs in the process of grabbing investment projects, we launch another test, and the results are presented in Table 9. This test partitions all the SOEs into central government controlled firms (central SOEs) and local government controlled firms (local SOEs) using the dummy variable central

SOE, which equals one, if the firm's ultimate ownership belongs to the central government of China, and zero otherwise. If the priority of SOEs substantially exists, conditional on the agency issue being mitigated by financial constraints, the central SOEs would obtain a higher quality of innovation investment projects and innovative talents due to their higher level of hierarchy, which will make central SOEs more efficient in their R&D investment activities than local SOEs. Table 8 Panel A indicates central SOEs are more innovatively efficient than local SOEs. The results of Table 9 Panel B further show that central SOEs perform significantly better in innovative efficiency than local SOEs, for those firms with more financial constraints. For example, the coefficients of central SOES are 0.080, 0.111, and 0.069, which represent a50.1%, 69.6%, and 43.3%, respectively, higher innovative efficiency for financially constrained central SOEs than local SOEs.

[INSERT TABLE 10 ABOUT HERE]

Table 10 presents evidence similar to Table 5 with subsamples by year. The results are quite stable over each of the years, from 2010-2013, and consistent with those reported in Table 3. The results from 2009, however, are insignificant.

[INSERT TABLES 11-13ABOUT HERE]

We conduct additional robustness tests that are reported in Tables 11-13. In Tables 11 and 12 we group firms into subsamples by dividing firms according to the characteristics related to Tobin's Q, leverage, cash flow, tangible assets, intangible assets, capital expenditures, and cash holdings. The data indicate higher innovative efficiency among firms with high Tobin's Q (with more growth options), high leverage, high intangible and tangible assets, and low cash flows and low cash holdings. All these findings substantially support the argument that among firms with constrained access to capital in high-growth and high-tech sectors, SOEs are substantially more innovatively efficient than non-SOEs. In Table 13 we include additional control variables for direct government subsidies. The findings are likewise consistent with those discussed above.

[INSERT TABLE 14 ABOUT HERE]

Table 14 we report a difference-in-differences regression for a longer time period 2002-2013 relative to the prior regression tables, but without R&D expenses because, as discussed above, R&D expenses are not available in China for these earlier periods. The data indicate, consistent with Tan et al. (2015), that partial privatization through the split share structure reform increased patent outputs amongst the SOEs. But as discussed above, this evidence does not comment on the innovative efficiency of the firms. In the period after partial privatization, the evidence shown above is strongly consistent with SOEs being substantially more innovative efficient than their non-SOE counterparts.

5. Conclusion

In this paper, we investigated whether SOEs are more innovatively efficient, with respect to patents per R&D expense, than non-SOEs in China during a time when SOEs were partly privatized. Also, we examined possible reasons for the comparative differences in innovation efficiency between SOEs and non-SOEs by examining subsamples of the data. The data indicated that Chinese SOEs are more efficient in producing innovation than non-SOEs. The data further indicated that Chinese SOEs are particularly more innovatively efficient than non-SOEs among firms that are relatively more capital constrained. Chinese SOEs are also more innovatively efficient in high-tech industries and industries with more pronounced product market conditions.Chinese SOEs appear to be able to make use of the benefits of state ownership through connections with public universities and access to talent and technology to bring about a sustained commitment to R&D and superior patent outcomes.

Our empirical analysis of SOEs in China took place from 2009-2013, after which SOEs were partly privatized. We do not have a direct test of whether or not the partial privatization increased or decreased innovation efficiency in China due to the lack of R&D data in the pre-period. We only compare the innovation efficiency of SEO and non-SEOs in the post-partial privatization period. Further analyses could be carried out if R&D data became available for earlier periods. Likewise, further work might examine whether or not the results here are consistent in other countries.

The evidence of the superior innovation efficiency of partly privatized SOEs in China relative to non-SOEs is pertinent to academics, industries, and policy makers. It is crucial for SOEs to improve their corporate governance and reduce agency issues by means of either internal incentive and constraints or external monitoring so as to take more advantage of partial privatization. Policy makers could be aware that partial privatization has its advantage by keeping the state's controlling power athand. It is reasonable for partially privatized SOEs in their transition period to catch up with private firms in innovation because of these advantages. Besides this, the policy makers might also acknowledge that, in certain industries, especially industries of high product competition and high technology, the controlled portion of shares is necessary to promise an increase in efficiency.

Finally, for academia, our paper sheds light on the literature of privatization, innovative efficiency, and corporate governance. The data support the argument that there are synergies between public and private ownership of Chinese SOEs in ways that facilitate innovative efficiency. In addition, this research also proves the link between a SOE’s priority and innovative efficiency, revealing that a state-controlled power can be an advantage for efficiently producing innovation.

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Figure 1A: Innovation Efficiency for SOEs and non-SOEs over Time (2007 – 2015)

This figure plots the firm-year, the level mean of firms (SOEs vs. non-SOEs),the number of successful Type I patent applications, and the research and development expenses for the two datasets SIPO and CSMAR.

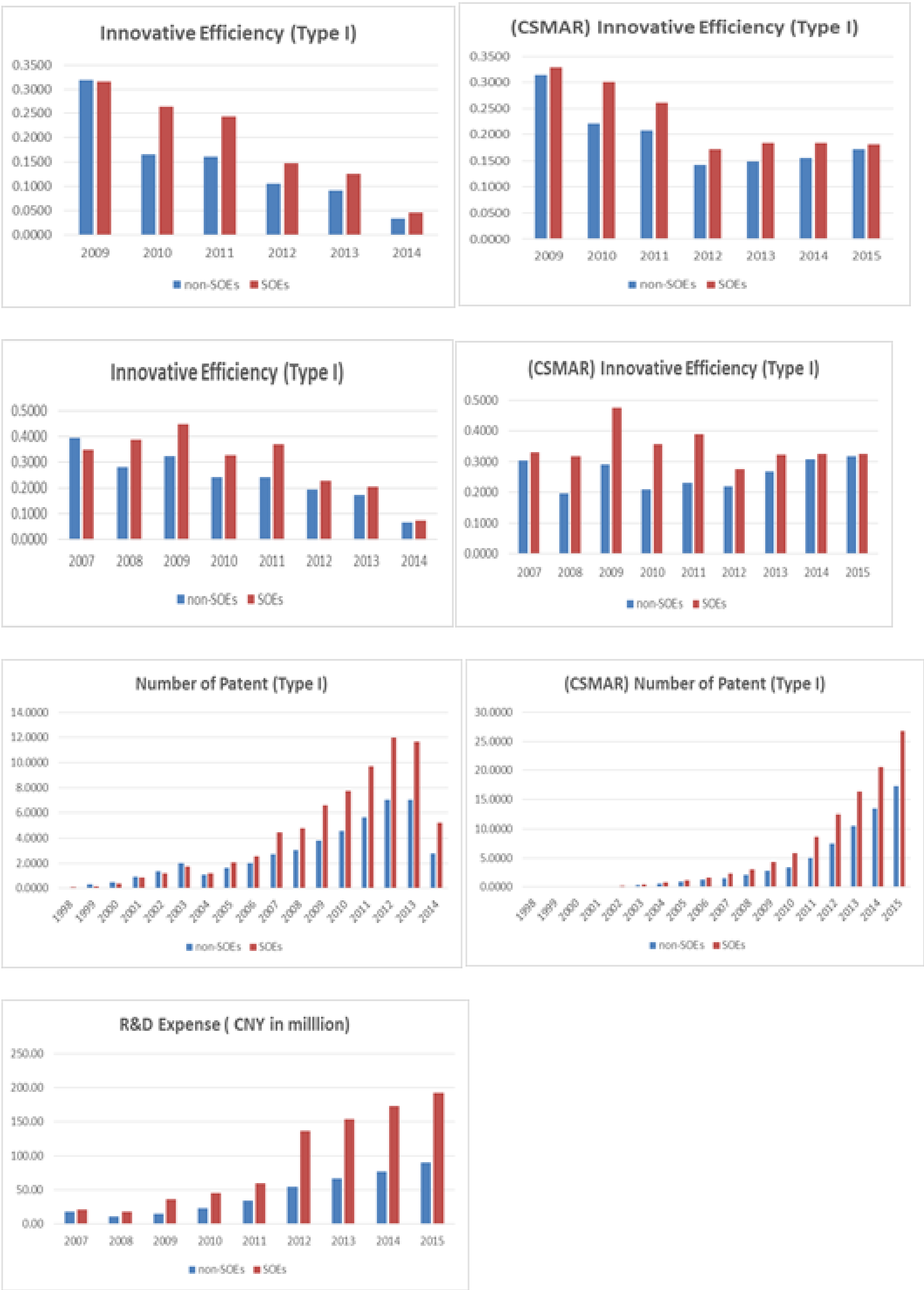

Table 1: Variable Definitions

Variable	Definition
Innovation measures	
Patent1	Total number of invention patent (Type I) applications filed and eventually granted in a given year. One source is from the State Intellectual Property Office (SIPO), and the other source is from China Stock Market & Accounting Research Database (CSMAR).
Patent all	Total number of invention patents (Type I), utility model patents (Type II), and appearance design patents (Type III) applications filed and eventually granted in a given year. One source is from the State Intellectual Property Office (SIPO), and the other source is from the China Stock Market & Accounting Research Database (CSMAR).
Innovative Efficiency	Innovative Efficiency (Hirschleifer, Hsu and Li, 2013) is calculated by taking the number of patents of firm*i* applied in year *t,* which eventually got granted, scaled by firm *i*'s cumulative R&D investment in the fiscal year ending in year *t*-2 through year *t*.
Control variables	
Firm Size	The logarithm of the book value of total assets measured at the end of fiscal year *t*.
Firm Age	The number of years the corporation has existed since getting listed.
Tobin's Q	The book value of total assets minus the book value of equity plus the market value of equity scaled by the book value of total assets at the end of the fiscal year t.
CAPEX	The capital expenditure divided by the book value of assets, measured at the end of fiscal year t-1.
ROA	The operating income before depreciation divided by the book value of total asset, measured at the end of fiscal year t-1.
Cash Flow	The income before extraordinary items plus depreciation and amortization divided by the book value of assets, measured at the end of fiscal year t-1.
Leverage	The book value of debt divided by the book value of total assets measured at the end of fiscal year t-1.
Tangibility	The book value of property, plant, and equipment divided by the book value of total assets measured at the end of fiscal year t-1.
Intangibility	The book value of intellectual property, including items such as patents, trademarks, copyrights, etc. divided by the book value of total assets measured at the end of fiscal year t-1.
R&DIntensity	The research and develop expenditure divided by the book value of assets, measured at the end of fiscal year t.
Revenue Growth	A firm's level annual sales growth rate.
Herfindahl Index	Herfindahl index of 2-digit level-2 industry code, provided by the China Security Regulation Commission (CSRC), of each firm measured at the end of fiscal year t based on sales.
High Tech Dummy	Indicator of whether or not firms qualifiedfor the high-tech requirement created by the government and, thus, received benefits like a tax deduction at the end of year t.

SOE Dummy	Indicator of whether or not the largest shareholder or the ultimate owner of the listed firms is state-owned at the end of year t.
Industry SOE Structure	The percentage of SOE firms in each industry.

Table 2: Summary Statistics

This table reports descriptive statistics for the sample of firms with innovation and firms characteristics data from1998to 2015. In Panel A, Columns (1) to (4) report the number of observations (N), mean, median, and standard deviation (S.D.) of the full sample. In Panel B, Columns (1) to (3) and (4) to (6) report the number of observations (N), mean,and standard deviation (S.D.) for subsamples of SOEs and non-SOEs,respectively. Column (7) reports the difference of mean for each variable between the two subsamples. In both Panels, the first variable is innovativeefficiency (Innov. Eff.) (Hirshleifer, Hsu and Li, 2013), which is defined by using the number of patent applications that areeventually granted divided by the R&D Expense of previous years. The other variables are the control variables: logarithm of total asset, firm age, Tobin's Q, returns on asset (ROA), cash flow, leverage, tangible assets,intangible assets, R&D intensityrevenue growth, high-tech dummy,and capital expenditure (CAPEX).Detailed definitions of each variable are provided in the Table 1 and ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: Full Sample

Variable	(1) N	(2) Mean	(3) Median	(4) S.D
Innovation Measures				
Patent 1	25,098	4.0196	0.0000	17.6838
Patent 1 (CSMAR)	25,098	6.7058	0.0000	28.1269
Inno. Eff.	10,397	0.1244	0.0000	0.3837
Inno. Eff. (CSMAR)	10,397	0.1970	0.0417	0.5163
Key Variables				
SOE Dummy	25,075	0.4622	0.0000	0.4986
log(Total Assets)	23,340	21.3980	21.2443	1.2358
Firm Age	25,093	11.5529	11.0000	5.6250
Tobin's Q	24,237	2.3776	1.8495	1.7609
CAPEX	23,340	0.0694	0.0448	0.0802
ROA	21,073	0.0451	0.0394	0.0825
Cash Flow	20,437	0.0790	0.0699	0.0836
Leverage	23,274	0.2172	0.1901	0.1921
Tangibility	23,340	0.3040	0.2680	0.1950
Intangibility	23,340	0.0543	0.0347	0.0681
R&D Intensity	10,974	0.0225	0.0172	0.0226
Revenue Growth	21,050	0.2058	0.1270	0.5594
High Tech Dummy	24,873	0.5943	1.0000	0.4910

Panel B: Subsample (SOE vs. Non-SOE)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)		(8)
	SOEs			non-SOEs					
	N	Mean	S.D	N	Mean	S.D	Mean-Diff		T-test
Patent Num	11,589	4.7064	20.6559	13,486	3.4327	14.6472	1.2738	***	5.69
Patent Num (CSMAR)	11,589	7.1404	32.1201	13,486	6.3396	32.1201	0.8008	**	2.25
Inno. Eff.	4,255	0.1595	0.4518	6,142	0.1001	0.3261	0.0594	***	7.79
Inno. Eff. (CSMAR)	4,255	0.2164	0.5771	6,142	0.1836	0.4692	0.0328	***	3.19
log(Total Assets)	11,078	21.7432	0.0127	12,240	21.0873	1.0418	0.6559	***	41.97
Firm Age	11,584	11.5288	5.7101	13,486	11.5670	5.5449	-0.0382		-0.53
Tobin's Q	11,379	2.0557	1.3695	12,838	2.6616	2.0003	-0.6060	***	-27.16
CAPEX	11,078	0.0675	0.0788	12,240	0.0712	0.0815	-0.0037	***	-3.47
ROA	10,276	0.0420	0.0420	10,776	0.0481	0.0890	-0.0061	***	-5.37
Cash Flow	10,022	0.0771	0.0786	10,394	0.0808	0.0881	-0.0037	***	3.13
Leverage	11,043	0.2305	0.1889	12,209	0.2047	0.1934	0.0258	***	10.26
Tangibility	11,078	0.3359	0.2078	12,240	0.2754	0.1777	0.0605	***	23.94
Intangibility	11,078	0.0511	0.0700	12,240	0.0570	0.0661	-0.0059	***	-6.62
R&D Intensity	4,138	0.0174	0.0208	6,836	0.0256	0.0230	-0.0082	***	-18.73
Revenue Growth	10,271	0.2009	0.5329	10,759	0.2102	0.5823	-0.0093		1.20
High Tech Dummy	11,477	0.5360	0.4987	13,396	0.6441	0.4788	-0.1081	***	17.42

Table 3: Main Regression, Propensity Score Matching, and Heckman MLE test

In this table, columns (1) and (2) report the baseline results of the OLS regression to test the effect of state ownership on innovativeefficiency. Columns (3) and (4) report propensity score matching results for SOEs versus non-SOEs. While in columns (5) and (6), the results of the Heckman Selection MLE regressions are reported. The dependent variables in column (1), (3), and (5)areinnovativelyefficientbased in SIPO, while columns (2), (4), and (6) use CSMAR. Innovative efficiency is defined by using the number of patent applications that areeventually granted divided by the R&D Expense of previous years. The main independent variable is an SOE Dummy that equals one, if a firm's ultimate controlling shareholders are the state or government agents in year t, and zero otherwise. It controls the logarithm of total asset, firm age, Tobin's Q, return on asset (ROA), cash flow, leverage, tangible assets, capital expenditure (CAPEX), as well as year and level-2 industry code, provided by the China Security Regulation Commission (CSRC) andfixed effects for year and industry. For the selection variable regressions (5) and (6), the dependent variable is an SOE Dummy and the independent variable is Herfindahl Index, high-tech Dummy, and industry SOE structure, which equals the natural logarithm of (1 + number of SOEs in certain industry / total number of SOEs in certain industry). It also controls for both industry and year fixed effect.Standard errors clustered at the industry level are reported in parentheses. Detailed definitions of each variable are provided in the Table 1 and ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Innov. Eff.	Innov. Eff. (CSMAR)	Innov. Eff.	Innov. Eff. (CSMAR)	Innov. Eff.	Innov. Eff. (CSMAR)
	OLS		OLS (PSM)		Heckman	
	(1)	(2)	(3)	(4)	(5)	(6)
SOE Dummy	0.036***	0.055***	0.053***	0.076***	0.279***	0.279***
	(0.011)	(0.015)	(0.011)	(0.015)	(0.020)	(0.020)
Log(Firm Age)	0.019*	0.008	0.012	0.021	0.021*	0.011
	(0.009)	(0.013)	(0.009)	(0.013)	(0.012)	(0.015)
Log(Total Assets)	-0.010**	-0.035***	-0.013**	-0.038***	-0.008*	-0.033***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
Lag(Tobin's Q)	-0.007**	-0.011***	-0.006*	-0.008*	-0.007*	-0.011**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
SalesGrowth	-0.013	-0.019	-0.023*	-0.041***	-0.013	-0.018
	(0.013)	(0.016)	(0.013)	(0.014)	(0.012)	(0.016)
ROA	-0.507*	-0.015	-0.274	0.047	-0.515	-0.027
	(0.303)	(0.380)	(0.311)	(0.437)	(0.334)	(0.433)
Cash Flow	0.358	-0.276	0.238	-0.265	0.362	-0.271
	(0.298)	(0.382)	(0.313)	(0.441)	(0.326)	(0.424)
Tangibility	-0.111**	-0.037	-0.106**	-0.069	-0.111***	-0.037
	(0.043)	(0.058)	(0.042)	(0.061)	(0.041)	(0.053)
Leverage	0.205***	0.190***	0.232***	0.235***	0.205***	0.189***
	(0.043)	(0.052)	(0.046)	(0.057)	(0.030)	(0.039)
High Tech Dummy	0.044***	0.059***	0.031***	0.060***	0.038***	0.050***
	(0.012)	(0.015)	(0.011)	(0.015)	(0.011)	(0.014)
Herfindahl Index	0.269	0.192	-0.131	-0.059	0.219	0.115
	(0.221)	(0.179)	(0.304)	(0.273)	(0.228)	(0.296)

Industry SOE Structure	0.107	-0.006	-0.313	-0.379	1.370**	1.928**
	(0.688)	(0.674)	(1.027)	(1.126)	(0.679)	(0.882)
Constant	0.305	0.889	0.800	1.371	-1.043*	-0.789
	(0.642)	(0.634)	(0.934)	(1.034)	(0.551)	(0.716)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Selection Model					SOE Dummy	
High Tech Dummy					0.059***	0.059***
					(0.020)	(0.020)
Herfindahl Index					0.078	0.078
					(0.097)	(0.097)
Industry SOE Structure					-11.941***	-11.941***
					(0.177)	(0.177)
Constant					10.185***	10.185***
					(0.158)	(0.158)
N	8178	8178	7074	7074	22448	22448
adj. R-sq	0.071	0.043	0.069	0.047		
Wald Test (Chi-sq p-value)					0.0000	0.0000

Table 4: Main Regressionwith Different Financial Constraints Variables

This table reports the estimation results of regressions designed to measure the effect of state ownership on innovation efficiency for firms with different financial constraints. We regress firm innovation efficiency in year t on an SOE Dummy variable that equals one, if a firm's ultimate controlling shareholders are the state or government agents in year t, and zero otherwise, and the product of the SOE Dummy variable with three different proxiesof financial constraints (theKZ Index, the WW Index,and the Dividend Dummy) for each firm in each year.The Dividend Dummy equals to one, if firms pays dividend to the shareholder at the given year. The dependent variables are the innovativeefficiency. All regressions control for the logarithm of total asset, firm age, Tobin's Q, return on asset (ROA), cash flow, leverage, tangible assets, and capital expenditure (CAPEX), high-tech dummy, Herfindahl index, industry SOE structure as well as year and level-2 industry code, provided by the China Security Regulation Commission (CSRC), fixed effects. Detailed definitions of each variable are provided in the Table 1. Standard errors clustered at theindustry level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Innovative Efficiency		
	(1)	(2)	(3)
SOE Dummy	0.013	0.292**	0.057***
	(0.013)	(0.147)	(0.014)
SOE*KZ Index	0.060***		
	(0.022)		
KZ Index	0.007		
	(0.014)		
SOE*WW Index		0.259*	
		(0.146)	
WW Index		0.333**	
		(0.167)	
SOE*Div Dummy			-0.032*
			(0.017)
Div Dummy			0.362
			(1.701)
Log(Firm Age)	0.019**	0.022**	0.018*
	(0.010)	(0.010)	(0.009)
Log(Total Assets)	-0.008*	0.014*	-0.009**
	(0.005)	(0.008)	(0.004)
Lag(Tobin's Q)	-0.011**	-0.007*	-0.007**
	(0.005)	(0.004)	(0.004)
SalesGrowth	-0.007	0.008	-0.016
	(0.012)	(0.014)	(0.012)
ROA	-0.488	-0.491	-0.442
	(0.303)	(0.302)	(0.299)
Cash Flow	0.323	0.408	0.340
	(0.291)	(0.298)	(0.298)
Tangibility	-0.113**	-0.113***	-0.101**
	(0.044)	(0.043)	(0.043)
Leverage	0.164***	0.213***	0.192***
	(0.041)	(0.043)	(0.042)
High Tech Dummy	0.044***	0.040***	0.040***
	(0.012)	(0.012)	(0.012)

Herfindahl Index	0.304	0.236	0.241
	(0.233)	(0.223)	(0.226)
Industry SOE Structure	0.232	-0.032	0.028
	(0.693)	(0.687)	(0.665)
Constant	0.204	-0.024	0.361
	(0.645)	(0.598)	(0.622)
Year F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
N	8001	8178	8047
adj. R-sq	0.072	0.072	0.067

Table 5: Financial Constraint Subsets

This table reports the estimation results of subsample regressions examining the effect of state ownership on innovation efficiency for firms with different financial constraints. We use the KZ index, the WW Index, and the Dividend Dummy as three proxies for the financial constraint. Column (1), (3), and (5) include all financially constrained subsamples, defined as firms with a KZ index above median, a WW Index above median, and firms that do not pay dividend, respectively. While column (2), (4), and (6) include all financial unconstrained subsamples, defined as firms with a KZ index below median, a WW Index below median, and firms that pay dividend, respectively. The dependent variable is the innovation efficiency; the main explanatory variable is an SOE Dummy. The regressions control for the logarithm of total asset, firm age, Tobin's Q, return on asset (ROA), cash flow, leverage, tangible assets, and capital expenditure (CAPEX), high-tech dummy, Herfindahl index, industry SOE structure as well as year and level-2 industry code, provided by the China Security Regulation Commission (CSRC), fixed effects. Detailed definitions of each variable are provided in the Table 1. . Standard errors clustered at the industry level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Innovative Efficiency					
	KZ Index		WW Index		Dividend Dummy	
	constrained	unconstrained	constrained	unconstrained	non dividend payer	dividend payer
	(1)	(2)	(3)	(4)	(5)	(6)
SOE Dummy	0.074***	-0.002	0.053***	0.026**	0.040**	0.035**
	(0.016)	(0.016)	(0.020)	(0.013)	(0.016)	(0.016)
Log(Firm Age)	0.016	0.025**	0.023	0.025**	0.035***	0.012
	(0.015)	(0.012)	(0.014)	(0.012)	(0.013)	(0.015)
Log(Total Assets)	-0.017**	0.002	0.001	-0.003	-0.013*	-0.002
	(0.007)	(0.006)	(0.012)	(0.006)	(0.007)	(0.007)
Lag(Tobin's Q)	-0.013***	-0.004	-0.009**	-0.005	-0.013***	-0.000
	(0.005)	(0.008)	(0.005)	(0.006)	(0.005)	(0.006)
SalesGrowth	-0.028*	0.015	0.022	-0.018	-0.019	-0.005
	(0.015)	(0.018)	(0.029)	(0.015)	(0.014)	(0.023)
ROA	-1.120**	0.373	0.209	-0.863**	-0.513	-0.231
	(0.461)	(0.394)	(0.527)	(0.366)	(0.355)	(0.553)
Cash Flow	1.023**	-0.648*	-0.376	0.764**	0.331	0.110

	(0.454)	(0.354)	(0.509)	(0.369)	(0.348)	(0.547)
Tangibility	-0.168***	0.005	-0.124*	-0.103*	-0.199***	0.036
	(0.060)	(0.062)	(0.064)	(0.059)	(0.053)	(0.078)
Leverage	0.256***	0.068	0.265***	0.184***	0.238***	0.158**
	(0.063)	(0.052)	(0.073)	(0.053)	(0.058)	(0.063)
High Tech Dummy	0.021	0.069***	0.030	0.054***	0.031*	0.055***
	(0.018)	(0.016)	(0.020)	(0.015)	(0.017)	(0.018)
Herfindahl Index	-0.123	0.760**	0.302	0.129	0.239	0.336
	(0.357)	(0.319)	(0.298)	(0.298)	(0.227)	(0.425)
Industry SOE Structure	2.000*	-1.200	-0.095	-0.256	0.021	-0.097
	(1.100)	(0.927)	(1.131)	(0.862)	(1.126)	(0.867)
Constant	-1.266	1.337	0.016	0.189	0.545	0.303
	(0.991)	(0.885)	(0.991)	(0.767)	(1.042)	(0.822)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	4202	3799	4033	4145	5074	3104
adj. R-sq	0.065	0.094	0.072	0.074	0.079	0.062

Table 6: Location and Market Condition Subsamples

This table reports the estimation results of subsample regressions examining the effect of state ownership on innovation efficiency for firms with different headquarter locations, and by market conditions. Column (1) and (2) include firms with headquarters located in Shanghai, Beijing, and Shenzhen, and others. While column (3) and (4) include firms with headquarters located in the coastal area and others. Columns (5) and (6) present subsets by firms with headquarters in a special economic zone and others. Columns (7) and (8) present subsets by high market index vs. low market index respectively.The dependent variable is the innovation efficiency; the main explanatory variable is an SOE Dummy. The regressions control for the logarithm of total assets, firm age, Tobin's Q, return on assets (ROA), cash flow, leverage, tangible assets, and capital expenditure (CAPEX), high-tech dummy, Herfindahl index, industry SOE structure as well as year and level-2 industry code, provided by the China Security Regulation Commission (CSRC), fixed effects. Detailed definitions of each variable are provided in the Table 1. . Standard errors clustered at the industry level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%,and 10% levels, respectively.

	Innovative Efficiency							
	SH&BJ&SZ		Coastal		Special Economic Zone		Market Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Yes	No	Yes	No	Yes	No	High	Low
SOE Dummy	-0.029	0.050***	0.019	0.048***	0.012	0.037***	0.022	0.041**
	(0.022)	(0.013)	(0.014)	(0.016)	(0.019)	(0.013)	(0.016)	(0.019)
Log(Firm Age)	0.028	0.014	0.010	0.023	0.010	0.022**	0.005	0.022
	(0.021)	(0.011)	(0.013)	(0.014)	(0.018)	(0.011)	(0.018)	(0.024)
Log(Total Assets)	-0.009	-0.008	-0.012**	-0.006	-0.014*	-0.008	-0.016***	-0.001
	(0.007)	(0.006)	(0.005)	(0.008)	(0.007)	(0.006)	(0.005)	(0.009)
Lag(Tobin's Q)	-0.012**	-0.005	-0.009**	-0.005	-0.010*	-0.005	-0.004	-0.008
	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)	(0.004)	(0.005)	(0.007)
SalesGrowth	-0.013	-0.014	-0.005	-0.021	-0.002	-0.016	0.007	-0.039*
	(0.020)	(0.015)	(0.014)	(0.020)	(0.018)	(0.016)	(0.021)	(0.022)
ROA	-0.931**	-0.086	-1.081***	0.224	0.388	-0.371	-0.807*	-0.592
	(0.457)	(0.381)	(0.362)	(0.504)	(0.601)	(0.355)	(0.468)	(0.553)
Cash Flow	0.808*	-0.060	0.976***	-0.407	-0.509	0.226	0.648	0.427

	(0.425)	(0.378)	(0.338)	(0.511)	(0.565)	(0.353)	(0.444)	(0.546)
Tangibility	0.026	-0.116**	-0.142***	-0.064	0.052	-0.130**	-0.160**	-0.111
	(0.068)	(0.053)	(0.053)	(0.064)	(0.074)	(0.051)	(0.065)	(0.080)
Leverage	0.102	0.225***	0.045	0.271***	-0.009	0.255***	0.150**	0.277***
	(0.075)	(0.050)	(0.054)	(0.061)	(0.060)	(0.052)	(0.065)	(0.071)
High Tech Dummy	0.035	0.041***	0.033*	0.041**	0.009	0.043***	0.046***	0.030
	(0.025)	(0.013)	(0.017)	(0.016)	(0.020)	(0.014)	(0.017)	(0.020)
Herfindahl Index	0.674	0.063	0.541*	0.028	0.555	0.156	0.572*	-0.142
	(0.445)	(0.252)	(0.279)	(0.363)	(0.449)	(0.259)	(0.325)	(0.308)
Industry SOE Structure	-0.552	0.347	0.329	-0.604	-1.438	0.490	0.445	-0.901
	(1.381)	(0.759)	(0.940)	(1.012)	(1.600)	(0.701)	(1.022)	(0.896)
Constant	0.885	0.061	0.186	0.819	1.929	-0.038	0.191	0.980
	(1.301)	(0.702)	(0.861)	(0.953)	(1.491)	(0.651)	(0.942)	(0.849)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1787	6391	3636	4542	1945	6233	3360	3273
adj. R-sq	0.130	0.069	0.081	0.080	0.118	0.072	0.091	0.071

Table 7: Market Competition

This table reports the estimation results of subsample regressions examining the effect of state ownership on innovation efficiency for firms in a product market with different levels of competition in different industry categories. Herfindahl Index (H-Index) is used to proxy for the product market competition. Firms with H-Index lower than the median are considered in the high competitive product market while the other in the low competitive product market. These two groups are included in column (1) and (2), respectively. While column (3) uses the full sample and addsthe variable Hindex and the interaction term SOE*Hindex. The dependent variable is the innovativeefficiency; the main explanatory variable is an SOE Dummy for column (1) and (2) and SOE*Hindex for column (3). The dependent variable is the innovation efficiency; the main explanatory variable is an SOE Dummy. The regressions control for the logarithm of total asset, firm age, Tobin's Q, return on asset (ROA), cash flow, leverage, tangible assets, and capital expenditure (CAPEX), high-tech dummy, industry SOE structure as well as year and level-2 industry code, provided by the China Security Regulation Commission (CSRC), fixed effects. Detailed definitions of each variable are provided in the Table 1. . Standard errors clustered at the industry level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	LV1 Industry			LV2 Industry			LV3 Industry			LV4 Industry		
	Innovative Efficiency											
	High Comp.	Low Comp.	Full	High Comp.	Low Comp.	Full	High Comp.	Low Comp.	Full	High Comp.	Low Comp.	Full
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
SOE Dummy	0.028**	0.047**	0.038***	0.031*	0.045***	0.037***	0.021	0.060***	0.016	0.033**	0.040**	0.019
	(0.014)	(0.019)	(0.012)	(0.017)	(0.014)	(0.014)	(0.016)	(0.016)	(0.014)	(0.016)	(0.016)	(0.014)
SOE*Hindex			-0.042			-0.017			0.234**			0.135**
			(0.062)			(0.087)			(0.098)			(0.066)
Hindex			0.140			0.278			-0.029			-0.073**
			(0.338)			(0.223)			(0.075)			(0.034)
Log(Firm Age)	0.021*	0.014	0.019*	0.027	0.010	0.019*	0.008	0.034***	0.019**	0.007	0.036**	0.018*
	(0.012)	(0.015)	(0.009)	(0.017)	(0.010)	(0.009)	(0.014)	(0.012)	(0.009)	(0.013)	(0.014)	(0.009)
Log(Total Assets)	-0.008	-0.010	-0.010**	-0.008	-0.011**	-0.010**	-0.012	-0.007	-0.011**	-0.019***	-0.002	-0.010**
	(0.006)	(0.007)	(0.005)	(0.008)	(0.005)	(0.005)	(0.007)	(0.006)	(0.005)	(0.007)	(0.006)	(0.005)
Lag(Tobin's	-0.006	-0.008	-0.007**	-0.006	-0.008	-0.007**	-0.001	-0.011**	-0.007**	-0.003	-0.013**	-0.007**

Q)												
	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)	(0.006)	(0.004)
SalesGrowth	-0.002	-0.021	-0.013	0.006	-0.029**	-0.013	-0.007	-0.021	-0.014	-0.018	-0.010	-0.014
	(0.019)	(0.019)	(0.013)	(0.023)	(0.013)	(0.013)	(0.018)	(0.018)	(0.013)	(0.014)	(0.021)	(0.013)
ROA	-0.673	-0.407	-0.500*	-0.527	-0.460	-0.508*	-0.487	-0.457	-0.489	-0.328	-0.633	-0.505*
	(0.474)	(0.386)	(0.304)	(0.463)	(0.395)	(0.303)	(0.460)	(0.386)	(0.303)	(0.509)	(0.386)	(0.303)
Cash Flow	0.513	0.244	0.354	0.282	0.415	0.360	0.309	0.343	0.340	0.194	0.468	0.354
	(0.487)	(0.356)	(0.299)	(0.471)	(0.371)	(0.298)	(0.467)	(0.363)	(0.298)	(0.515)	(0.363)	(0.299)
Tangibility	-0.109**	-0.132*	-0.110**	-0.087	-0.147**	-0.111**	-0.064	-0.156**	-0.109**	-0.097	-0.145**	-0.113***
	(0.055)	(0.075)	(0.044)	(0.063)	(0.059)	(0.043)	(0.062)	(0.061)	(0.043)	(0.063)	(0.064)	(0.044)
Leverage	0.157***	0.279***	0.205***	0.156**	0.262***	0.205***	0.184***	0.234***	0.208***	0.240***	0.186***	0.205***
	(0.050)	(0.078)	(0.043)	(0.064)	(0.055)	(0.043)	(0.061)	(0.060)	(0.043)	(0.061)	(0.061)	(0.043)
High Tech Dummy	0.026*	0.074***	0.043***	0.028	0.064***	0.044***	0.022	0.073***	0.045***	0.023	0.061***	0.043***
	(0.015)	(0.019)	(0.012)	(0.019)	(0.014)	(0.012)	(0.018)	(0.016)	(0.012)	(0.018)	(0.016)	(0.012)
Industry SOE Structure	-0.406	-0.663	0.093	0.224	0.211	0.107	-0.403	-0.018	0.084	-0.668	0.512	0.116
	(1.224)	(1.021)	(0.689)	(1.125)	(0.966)	(0.688)	(0.983)	(1.162)	(0.684)	(1.037)	(0.916)	(0.686)
Constant	0.821	0.973	0.327	0.187	0.234	0.303	0.932	0.345	0.375	1.271	-0.193	0.332
	(1.173)	(0.943)	(0.643)	(1.044)	(0.887)	(0.642)	(0.916)	(1.072)	(0.640)	(0.962)	(0.860)	(0.640)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5038	3140	8178	3988	4190	8178	4453	3725	8178	4438	3740	8178
adj. R-sq	0.077	0.067	0.070	0.072	0.067	0.071	0.077	0.068	0.071	0.075	0.074	0.071

Table 8: High-Technology Industry

This table reports the estimation results of subsample regressions examining the effect of state ownership on innovation efficiency for firms in high-tech industries or not. We adopt Hall and Lerner's (2010) taxonomy where the high-technology sector comprises pharmaceuticals, office and computing equipment, communications equipment, and electronic components. Column (1) and (2) include firms in high-tech industries and non-high-tech industries, respectively. While column (3) uses the full sample to do difference-in-difference test by adding the variable High-Tech Dummy and the interaction term SOE*Hi-Tech. The dependent variable is the innovation efficiency; the main explanatory variable is an SOE Signal for column (1) and (2) and SOE*High-Tech for column (3). The dependent variable is the innovation efficiency; the main explanatory variable is an SOE Dummy. The regressions control for the logarithm of total asset, firm age, Tobin's Q, return on asset (ROA), cash flow, leverage, tangible assets, and capital expenditure (CAPEX), Herfindahl index, industry SOE structure as well as year and level-2 industry code, provided by the China Security Regulation Commission (CSRC), fixed effects. Detailed definitions of each variable are provided in the Table 1. . Standard errors clustered at the industry level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Innovative Efficiency		
	High Tech	non High Tech	Full
	(1)	(2)	(3)
SOE Dummy	0.051***	0.021	0.026
	(0.013)	(0.022)	(0.019)
SOE*HighTech			0.051***
			(0.017)
nonSOE*HighTech			0.036**
			(0.015)
Log(Firm Age)	0.023**	0.007	0.018*
	(0.011)	(0.019)	(0.009)
Log(Total Assets)	-0.018***	-0.009	-0.010**
	(0.006)	(0.007)	(0.005)
Lag(Tobin's Q)	-0.008*	-0.010*	-0.007**
	(0.005)	(0.006)	(0.004)
SalesGrowth	-0.003	-0.019	-0.013
	(0.016)	(0.021)	(0.013)
ROA	0.550	-1.625***	-0.505*
	(0.382)	(0.557)	(0.303)
Cash Flow	-0.586	1.382**	0.358
	(0.367)	(0.556)	(0.298)
Tangibility	-0.052	-0.193***	-0.111**
	(0.056)	(0.072)	(0.043)
Leverage	0.219***	0.216***	0.205***
	(0.054)	(0.074)	(0.043)
Herfindahl Index	0.166	0.485	0.267
	(0.304)	(0.302)	(0.221)
Industry SOE Structure	-0.792	0.957	0.092
	(0.978)	(0.919)	(0.688)
Constant	1.411	-0.422	0.323
	(0.903)	(0.858)	(0.642)
Year F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
N	5434	2744	8178
adj. R-sq	0.092	0.048	0.071

Table 9: Central-Government Owned Subsample

This table reports the estimation results of subsample regressions examining the effect of central government ownership on innovation efficiency for firms with different financial constraints. We use the KZ index, the WW Index, and the logarithm of total assets as three proxies for the financial constraint. Panel A reports the full sample. Panel B considers subsamples. In Panel B, columns (1), (3), and (5) include all financial constrained subsamples, defined as firms with a KZ index above median, a WW Index above median, and non-dividend payers, respectively. Panel B columns (2), (4), and (6) include all financial unconstrained subsamples, defined as firms with a KZ index below median, a WW Index below median, and non-dividend payers, respectively. The dependent variable is the innovation efficiency; the main explanatory variable is an SOE Signal for column (1) and (2) and SOE*High-Tech for column (3). The dependent variable is the innovation efficiency; the main explanatory variable is an SOE Dummy. The regressions control for the logarithm of total asset, firm age, Tobin's Q, return on asset (ROA), cash flow, leverage, tangible assets, and capital expenditure (CAPEX), Herfindahl index, industry SOE structure as well as year and level-2 industry code, provided by the China Security Regulation Commission (CSRC), fixed effects. Detailed definitions of each variable are provided in the Table 1. . Standard errors clustered at industry level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A : Full Sample	Innovative Efficiency		
	(1)	(2)	(3)
Central-SOE Dummy	0.016	0.651***	0.084***
	(0.021)	(0.200)	(0.024)
Central-SOE*KZ Index	0.086**		
	(0.041)		
KZ Index	0.021*		
	(0.013)		
Central-SOE*WW Index		0.593***	
		(0.192)	
WW Index		0.322**	
		(0.155)	
Central-SOE*Div Dummy			-0.052
			(0.032)
Div Dummy			0.061
			(1.653)
Log(Firm Age)	0.024***	0.023**	0.022**
	(0.009)	(0.009)	(0.009)
Log(Total Assets)	-0.007	0.014*	-0.007
	(0.005)	(0.008)	(0.004)
Lag(Tobin's Q)	-0.012***	-0.007**	-0.008**
	(0.005)	(0.004)	(0.004)
SalesGrowth	-0.007	0.006	-0.016
	(0.012)	(0.014)	(0.012)
ROA	-0.492	-0.520*	-0.482
	(0.305)	(0.305)	(0.303)
Cash Flow	0.312	0.417	0.370
	(0.292)	(0.298)	(0.300)
Tangibility	-0.112**	-0.110**	-0.099**

	(0.044)	(0.043)	(0.043)
Leverage	0.166***	0.212***	0.193***
	(0.041)	(0.043)	(0.042)
High Tech Dummy	0.043***	0.036***	0.038***
	(0.012)	(0.012)	(0.012)
Herfindahl Index	0.306	0.235	0.234
	(0.234)	(0.226)	(0.228)
Industry SOE Structure	0.262	-0.018	0.077
	(0.690)	(0.686)	(0.666)
Constant	0.126	-0.046	0.287
	(0.644)	(0.596)	(0.624)
Year F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
N	8001	8178	8047
adj. R-sq	0.072	0.073	0.067

Panel B: Subsample	Innovative Efficiency					
	KZ Index		WW Index		Dividend Dummy	
	constrained	unconstrained	constrained	unconstrained	non dividend payer	dividend payer
	(1)	(2)	(3)	(4)	(5)	(6)
Central-SOE Dummy	0.080***	0.027	0.111***	0.026	0.069***	0.039
	(0.026)	(0.023)	(0.034)	(0.020)	(0.025)	(0.025)
Log(Firm Age)	0.028*	0.024**	0.024*	0.031***	0.038***	0.019
	(0.015)	(0.012)	(0.014)	(0.012)	(0.012)	(0.015)
Log(Total Assets)	-0.014*	-0.000	0.002	-0.002	-0.011	-0.001
	(0.007)	(0.006)	(0.012)	(0.006)	(0.007)	(0.007)
Lag(Tobin's Q)	-0.013***	-0.005	-0.010**	-0.005	-0.013***	-0.000
	(0.005)	(0.008)	(0.005)	(0.006)	(0.005)	(0.006)
SalesGrowth	-0.028*	0.014	0.021	-0.017	-0.020	-0.004
	(0.015)	(0.018)	(0.028)	(0.016)	(0.014)	(0.023)
ROA	-1.165**	0.397	0.229	-0.903**	-0.548	-0.248
	(0.466)	(0.400)	(0.526)	(0.372)	(0.359)	(0.558)
Cash Flow	1.050**	-0.664*	-0.400	0.789**	0.357	0.119
	(0.456)	(0.359)	(0.507)	(0.372)	(0.349)	(0.550)
Tangibility	-0.170***	0.008	-0.110*	-0.105*	-0.198***	0.036
	(0.060)	(0.062)	(0.064)	(0.060)	(0.053)	(0.078)
Leverage	0.257***	0.069	0.265***	0.182***	0.240***	0.152**
	(0.063)	(0.052)	(0.072)	(0.053)	(0.058)	(0.063)
High Tech Dummy	0.017	0.069***	0.023	0.053***	0.028*	0.054***
	(0.017)	(0.016)	(0.020)	(0.015)	(0.017)	(0.018)
Herfindahl Index	-0.148	0.772**	0.300	0.116	0.251	0.299
	(0.355)	(0.319)	(0.307)	(0.298)	(0.230)	(0.426)
Industry SOE Structure	2.095*	-1.238	-0.062	-0.263	0.081	-0.106
	(1.097)	(0.924)	(1.125)	(0.865)	(1.120)	(0.870)
Constant	-1.424	1.419	-0.015	0.176	0.447	0.298
	(0.991)	(0.877)	(0.986)	(0.771)	(1.035)	(0.829)

Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	4202	3799	4033	4145	5074	3104
adj. R-sq	0.063	0.094	0.074	0.073	0.079	0.062

Table 10: Cross-Year Test

This table reports the estimation results of subsample cross sectional regressions examining the effects of state ownership on innovation efficiency across years during 2009 – 2013 for firms with different financial constraints. All the control variables are omitted to be concise. We use the KZ index, the WW Index, and a Dividend Dummy as three proxies for the financial constraint. Column (1), (3), and (5) include all financially constrained subsamples, defined as firms with a KZ index above median, a WW Index above median, and firms do not pay dividend, respectively. While column (2), (4), and (6) include all financial unconstrained subsamples, defined as firms with a KZ index below median, a WW Index below median, and firms pay dividend, respectively. The dependent variable is the innovation efficiency; the main explanatory variable is an SOE Dummy. The regressions control for the logarithm of total assets, firm age, Tobin's Q, return on asset (ROA), cash flow, leverage, tangible assets, and capital expenditure (CAPEX), high-tech dummy, Herfindahl index, industry SOE structure,as well as year and level-2 industry code, provided by the China Security Regulation Commission (CSRC), fixed effects. Detailed definitions of each variable are provided in the Table 1. . Standard errors clustered at industry level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Innovative Efficiency					
	KZ Index		WW Index		Dividend Dummy	
	constrained	unconstrained	constrained	unconstrained	non dividend payer	dividend payer
	(1)	(2)	(3)	(4)	(5)	(6)
Year 2009 (Obs: 1,478)						
SOE Dummy	-0.009	0.004	0.038	0.001	-0.019	0.066
	(0.091)	(0.083)	(0.087)	(0.092)	(0.082)	(0.101)
Central-SOE Dummy	-0.047	0.016	0.020	-0.014	-0.066	0.107
	(0.115)	(0.092)	(0.125)	(0.086)	(0.099)	(0.107)
Year 2010 (Obs: 1,828)						
SOE Dummy	0.202***	0.031	0.141**	0.098**	0.125**	0.107*
	(0.053)	(0.055)	(0.063)	(0.045)	(0.055)	(0.055)
Central-SOE Dummy	0.172*	0.087	0.283**	0.043	0.215**	0.058
	(0.089)	(0.075)	(0.123)	(0.057)	(0.091)	(0.080)
Year 2011 (Obs: 2,063)						
SOE Dummy	0.118**	0.042	0.186***	0.033	0.142***	0.027
	(0.050)	(0.038)	(0.061)	(0.045)	(0.051)	(0.049)
Central-SOE Dummy	0.043	-0.009	0.033	0.024	0.009	0.043

	(0.075)	(0.048)	(0.093)	(0.057)	(0.061)	(0.078)
Year 2012 (Obs: 2,191)						
SOE Dummy	0.080***	0.005	0.063*	0.039	0.058**	0.036
	(0.029)	(0.027)	(0.034)	(0.025)	(0.027)	(0.031)
Central-SOE Dummy	0.116**	-0.013	0.080*	0.060	0.093**	0.031
	(0.052)	(0.025)	(0.043)	(0.043)	(0.045)	(0.043)
Year 2013 (Obs: 2,239)						
SOE Dummy	0.097***	0.018	0.072*	0.051**	0.067**	0.041*
	(0.030)	(0.025)	(0.038)	(0.020)	(0.030)	(0.021)
Central-SOE Dummy	0.111*	0.008	0.133*	0.050	0.111*	0.032
	(0.058)	(0.040)	(0.075)	(0.046)	(0.057)	(0.050)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Subsets of Firms by Financial Measures

This table reports the estimation results of subsample regressions examining effects of state ownership on innovation efficiency for firms with firm characteristics regarding agency issue. Columns (1), (3), and (5) include all subsample firms with high (above median) Tobin's Q, high leverage, and high cash flow. While columns (2), (4), and (6) include all subsample firms with low (below median) Tobin's Q, low leverage, and low cash flows. The dependent variable is the innovativeefficiency; the main explanatory variable is an SOE Dummy. The regressions control for the logarithm of total asset, firm age, Tobin's Q, return on asset (ROA), cash flow, leverage, tangible assets, and capital expenditure (CAPEX), high-tech dummy, Herfindahl index, industry SOE structure,as well as year and level-2 industry code, provided by the China Security Regulation Commission (CSRC), fixed effects. Detailed definitions of each variable are provided in the Table 1. . Standard errors clustered at industry level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Innovative Efficiency					
	Tobin Q		Leverage		Cash Flow	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
SOE Dummy	0.058***	0.012	0.039**	0.032**	0.025*	0.054***
	(0.015)	(0.017)	(0.017)	(0.014)	(0.015)	(0.017)
Log(Firm Age)	0.002	0.045***	0.007	0.032***	0.001	0.029*
	(0.014)	(0.013)	(0.015)	(0.012)	(0.011)	(0.016)
Log(Total Assets)	-0.015**	-0.004	-0.005	-0.008	-0.001	-0.017**
	(0.007)	(0.007)	(0.007)	(0.005)	(0.006)	(0.007)
Lag(Tobin's Q)	-0.011***	0.010	-0.006	-0.007**	-0.011**	-0.009
	(0.004)	(0.030)	(0.008)	(0.004)	(0.004)	(0.008)
SalesGrowth	-0.022*	0.004	-0.020	0.000	-0.022	-0.009
	(0.014)	(0.025)	(0.019)	(0.016)	(0.016)	(0.022)
ROA	-0.147	-1.307**	-1.015**	0.403	-0.144	-1.193
	(0.346)	(0.599)	(0.432)	(0.455)	(0.308)	(0.789)
Cash Flow	0.056	0.991*	0.768*	-0.501	0.173	0.621
	(0.354)	(0.556)	(0.404)	(0.470)	(0.318)	(0.837)
Tangibility	-0.011	-0.248***	-0.164***	0.031	-0.075	-0.172**
	(0.058)	(0.071)	(0.058)	(0.063)	(0.056)	(0.073)
Leverage	0.171***	0.228***	0.268***	0.047	0.219***	0.193***
	(0.057)	(0.064)	(0.075)	(0.133)	(0.060)	(0.063)
High Tech Dummy	0.037**	0.049***	0.046***	0.036**	0.063***	0.030*
	(0.018)	(0.016)	(0.017)	(0.016)	(0.016)	(0.017)
Herfindahl Index	-0.146	0.684***	-0.138	0.492*	-0.051	0.724*
	(0.329)	(0.259)	(0.443)	(0.268)	(0.265)	(0.375)
Industry SOE Structure	1.184	-1.101	-0.295	0.650	1.006	-1.297
	(0.892)	(1.048)	(1.122)	(0.844)	(0.851)	(1.098)
Constant	-0.451	1.181	0.554	-0.217	-0.616	1.808*
	(0.816)	(1.003)	(1.057)	(0.772)	(0.798)	(1.025)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes

N	4084	4094	4172	4006	4145	4033
adj. R-sq	0.075	0.074	0.074	0.074	0.075	0.077

Table 12: Subsets of Data by Balance Sheet Variables

This table reports the estimation results of subsample regressions examining effect of state ownership on innovation efficiency for firms with firm characteristics regarding agency issue. Column (1), (3), (5), and (7) include all subsample firms with more tangible assets, more intangible assets, high capital expenditures, and high cash holdings, respectively, and low levels for columns (2), (4), (6), and(8). The dependent variable is the innovation efficiency; the main explanatory variable is SOE Dummy. The regressions control for the logarithm of total asset, firm age, Tobin's Q, return on asset (ROA), cash flow, leverage, tangible assets, and capital expenditure (CAPEX), high-tech dummy, Herfindahl index, industry SOE structure as well as year and level-2 industry code, provided by China Security Regulation Commission (CSRC), fixed effects. Detailed definitions of each variable are provided in the Table 1. . Standard errors clustered at industry level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Innovative Efficiency							
	Tangible Assets		Intangible Assets		Capital Expenditure		Cash Holding	
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SOE Dummy	0.044***	0.029*	0.040***	0.033**	0.027	0.050***	0.018	0.053***
	(0.017)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)
Log(Firm Age)	0.021	0.022*	0.009	0.027**	0.024*	0.012	0.017	0.022
	(0.015)	(0.012)	(0.014)	(0.013)	(0.012)	(0.015)	(0.012)	(0.016)
Log(Total Assets)	-0.013*	-0.008	-0.013**	-0.008	-0.002	-0.019***	-0.001	-0.018**
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
Lag(Tobin's Q)	-0.011**	-0.003	-0.005	-0.009*	-0.011**	-0.006	-0.005	-0.005
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.008)
SalesGrowth	-0.009	-0.008	-0.017	-0.001	-0.024	0.003	0.008	-0.028
	(0.017)	(0.018)	(0.017)	(0.019)	(0.017)	(0.020)	(0.016)	(0.019)
ROA	-0.322	-0.424	0.229	-1.339**	-0.360	-0.730	-0.096	-1.027**
	(0.390)	(0.485)	(0.330)	(0.641)	(0.347)	(0.684)	(0.382)	(0.501)
Cash Flow	0.170	0.318	-0.252	1.027*	0.320	0.493	-0.152	0.988**
	(0.379)	(0.472)	(0.327)	(0.623)	(0.331)	(0.698)	(0.363)	(0.495)
Tangibility	-0.132*	-0.091	-0.088*	-0.164**	-0.103*	-0.165*	-0.100*	-0.136**

	(0.068)	(0.131)	(0.053)	(0.078)	(0.053)	(0.084)	(0.060)	(0.067)
Leverage	0.168***	0.250***	0.197***	0.216***	0.219***	0.204***	0.167***	0.254***
	(0.055)	(0.071)	(0.055)	(0.069)	(0.057)	(0.067)	(0.059)	(0.063)
High Tech Dummy	0.031*	0.058***	0.036**	0.050***	0.046***	0.043***	0.075***	0.024
	(0.017)	(0.017)	(0.016)	(0.018)	(0.018)	(0.016)	(0.017)	(0.016)
Herfindahl Index	0.069	0.464	0.367	0.239	0.062	0.602	0.115	0.514
	(0.323)	(0.322)	(0.445)	(0.250)	(0.250)	(0.384)	(0.252)	(0.404)
Industry SOE Structure	0.056	-0.036	1.524*	-1.420	0.468	-0.258	0.537	-1.123
	(0.819)	(1.045)	(0.921)	(1.023)	(0.859)	(1.106)	(0.775)	(1.284)
Constant	0.480	0.343	-0.844	1.722*	-0.172	0.874	-0.255	1.563
	(0.784)	(0.957)	(0.856)	(0.959)	(0.816)	(1.014)	(0.710)	(1.212)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4177	4001	4254	3924	4250	3928	4058	4120
adj. R-sq	0.066	0.077	0.070	0.078	0.073	0.070	0.097	0.058

Table 13: Controlling for Other Government Subsidies

In this table, we report the baseline results of the OLS regression in **Table 2**includingsubsidies received from the government (Subsidies). The dependent variables in column (1) and (3) are innovation efficiency based in SIPO, while columns (2) and (4) use CSMAR. Innovation efficiency is defined by using the number of patent application that is eventually granted divided by the R&D Expense from previous years. The main independent variable is an SOE Dummy that equals one, if a firm's ultimate controlling shareholders are the state or government agents in year t, and zero otherwise. It controls the logarithm of total asset, firm age, Tobin's Q, return on asset (ROA), cash flow, leverage, tangible assets, capital expenditure (CAPEX), as well as year and level-2 industry code, provided by the China Security Regulation Commission (CSRC) andfixed effects for year and industry. Standard errors clustered at industry level are reported in parentheses. Detailed definitions of each variable are provided in the Table 1 and ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Innov. Eff.	Innov. Eff. (CSMAR)	Innov. Eff.	Innov. Eff. (CSMAR)
	(1)	(2)	(3)	(4)
SOE Dummy	0.035***	0.054***	0.033***	0.064***
	(0.011)	(0.015)	(0.010)	(0.013)
Subsidies/Lag(Total Assets)	0.435	0.157		
	(0.440)	(0.493)		
Subsidies/lag(R&D)			0.009***	0.013***
			(0.002)	(0.002)
Log(Firm Age)	0.019**	0.008	0.009	-0.003
	(0.009)	(0.013)	(0.008)	(0.012)
Log(Total Assets)	-0.009**	-0.034***	-0.016***	-0.041***
	(0.005)	(0.005)	(0.004)	(0.005)
Lag(Tobin's Q)	-0.008**	-0.012***	-0.002	-0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
SalesGrowth	-0.013	-0.019	-0.025**	-0.041***
	(0.013)	(0.016)	(0.011)	(0.015)
ROA	-0.514*	-0.018	-0.530*	0.063
	(0.303)	(0.381)	(0.288)	(0.369)
Cash Flow	0.357	-0.277	0.470	-0.233
	(0.298)	(0.382)	(0.288)	(0.382)
Tangibility	-0.113***	-0.038	-0.101***	-0.048
	(0.043)	(0.058)	(0.037)	(0.051)
Leverage	0.203***	0.189***	0.143***	0.130***
	(0.043)	(0.052)	(0.038)	(0.043)
High Tech Dummy	0.043***	0.059***	0.035***	0.073***
	(0.012)	(0.014)	(0.011)	(0.014)
Herfindahl Index	0.268	0.191	0.095	-0.060
	(0.221)	(0.179)	(0.257)	(0.189)
Industry SOE Structure	0.100	-0.008	-0.804	-0.452
	(0.688)	(0.672)	(0.793)	(0.784)
Constant	0.306	0.890	0.978	1.395**
	(0.642)	(0.633)	(0.679)	(0.672)
Year F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
N	8178	8178	6935	6935
adj. R-sq	0.071	0.043	0.090	0.080

Table 14: The Impact of Partial Privatization on Patents

This table reports the results of the DiD regressions designed for testing the effect of privatization on innovation (patents), not innovation efficiency. All regressions include firm and year fixed effects. The sample period is 2002-2013. R&D expenses are not included as they are not available for these sample years. After is a dummy variable equal to 1 for the years after partial privatization in 2005. Standard errors clustered at the industry level are reported in parentheses. Detailed definitions of each variable are provided in the Table 1 and ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	$lnPatent1_{t+4}$	$lnPatentall_{t+4}$	$lnPatent1_{t+4}$ (CSMAR)	$lnPatentall_{t+4}$ (CSMAR)
SOE*After	0.093**	0.035	0.124**	0.138**
	(0.037)	(0.045)	(0.058)	(0.070)
SOE Dummy	0.039	0.092*	-0.052	0.004
	(0.043)	(0.049)	(0.062)	(0.078)
After	0.326***	0.348***	-0.230**	-0.283**
	(0.062)	(0.074)	(0.091)	(0.111)
Leverage	-0.013	-0.059	0.086	0.138*
	(0.057)	(0.069)	(0.061)	(0.080)
Tangibility	0.020	0.028	0.104	0.046
	(0.054)	(0.067)	(0.069)	(0.093)
ROA	0.201**	0.273**	-0.173*	0.046
	(0.085)	(0.106)	(0.100)	(0.131)
Sales Growth	0.010	0.024*	-0.041***	-0.029**
	(0.010)	(0.013)	(0.009)	(0.013)
Log(Age)	0.027	0.107*	0.415***	0.654***
	(0.047)	(0.057)	(0.071)	(0.089)
Log(Sales)	0.027***	0.021**	0.078***	0.096***
	(0.007)	(0.009)	(0.013)	(0.016)
Constant	-0.292*	0.043	-1.708***	-1.811***
	(0.167)	(0.194)	(0.270)	(0.351)
Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
N	14456	14456	14456	14456
adj. R-sq	0.196	0.243	0.326	0.299