State Ownership and R&D Efficiency: Evidence from Chinese Listed Firms

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Abstract

The paper empirically investigates the impact of state ownership on the Efficiency of R&D at the firm level. We estimate the economic value of invention patents granted to Chinese publicly listed firms by the stock market's responses to the patent issuance, following the methodology proposed in Kogan, Papanikolaou, Seru and Stoffman (2017). We measure the return of R&D by dividing future patent value by current R&D expenditure, and find that the state-owned firms' R&D efficiency is higher with very low R&D intensity, and is lower for medium and high R&D intensity. This finding is robust across different specifications, with both non-parametric and parametric models.

1 Introduction

What is the role that state ownership plays in the efficiency of a firm's R&D activities? This question is in dispute by both theorists and empiricists, and contradicting evidence has been reported from different regions, industries, using various techniques. Facilitaed by a novel and precise method, proposed by Kogan et al. (2017), to estimate the economic value of innovation, we construct a database of the private value of patents granted to Chinese publicly listed firms, and employ it to shed new lights on the question aforementioned.

As early as in Schumpeter (1942), it is argued that in a planned economy, technological progress is more rapid than in a decentralized one, because the planner is not subject to a series of frictions that may impede a profit-maximizing enterpreneur to adopt a new technology as soon as possible. Equally eloquent is the counter-argument by Hayek (1968) (translated by Snow (2002)), that competition "allows a thousand flowers to bloom, and discovers the best among them"[1]. More reasons why state ownership leads to lower efficiency is reviewed in Vickers and Yarrow (1991). These conflicting theories are reconciled with an inverted-U relationship between competition and innovation (Aghion et al. (2005)), as well as between the degree of state ownership and firm performance (Sun, Tong and Tong (2003)). Within this theoretical framework, empirical findings with opposite claims can coexist without compromising each other, if we are willing to believe such discrepancy is due to the heterogeneity in the degree of state ownership across countries or industries.

Among these empirical researches on the relationship between state ownership and R&D performance, though some draw evidence from certain national (Vo (2018)), regional (Bortolotti, Fotak and Wolfe (2018)) or global data (Boubakri, Cosset and Saffar (2013)), most lay their focus on the Chinese economy, because of the vigorous symbiosis between its state-owned enterprises (SOEs) and non-state-owned enterprises (NSEs), and also of the resulting abundancy of data. The findings, however, are not unanimous. For example, Kroll and Kou (2019) confirms the inhibiting character of state ownership on Chinese listed firms' patent applications. Choi, Lee and Williams (2011) also uses the sample of Chinese listed firms, and finds a positive, but lagged influence of state ownership on innovation performance. Clò, Florio and Rentocchini (2020) looks at the Chinese telecommunication industry, and observes a positive correlation between public ownership and patenting activity. A few studies assert on specific channels through which state ownership exerts its impact: in Zhu and Yang (2016), state ownership is associated with more risk-taking in Chinese banking industry; Cai and

[1] See Bento (2014)

Tylecote (2008) again examines Chinese mobile telecommunication industry, and reports an improved access to finance of state-owned firms.

The above disagreement on the role of state ownership in innovation performance comes not only from the difference in sectors, which may be on different halves of the inverted-U curve; it also probably reflects the difference in measures of the quality of innovation. Measures used for Chinese patent quality includes patent number (Dang and Motohashi (2015)), patent renewal (Huang (2012), Zhang and Chen (2012), Thoma (2013), Liu, Cao and Song (2014), Zhang, Lv and Zhou (2014), Huang, Duan and Zhang (2020)), collateral value (Dang and Motohashi (n.d.)), international citations (Boeing and Mueller (2016)), citation lag (Fisch, Sandner and Regner (2017)) and self-reported patent quality (Mao, Johnston and Yin (2019)). Compared with the measure proposed by Kogan et al. (2017) (called the KPSS method in the rest of this paper), which estimate the patent value by the stock market's response, all of these measures are indirect and noisy, except the last one, which is subjective.

In this paper, we employ the novel method to estimate the economic value of invention patents[2] (referred to as "patents" in the rest of this paper) granted to Chinese publicly listed firms[3], and combine them with data on firm-year R&D expenditure to construct a measure of return of R&D (RRD). We then use this measure for the design of a few reduced-form empirical tests to see if and how state ownership affects firm's R&D efficiency. Both of our parametric and non-parametric models suggests that the role of state ownership in R&D efficiency depends on the R&D intensity (RDI): for firms with low (below the first quartile) RDI, the SOEs are more efficient in R&D; for firms with medium and high RDI, the SOEs are less R&D efficient. When we decompose the SOEs into the central and local levels, we find that the above RDI-dependent pattern is due to the impact from the local SOEs, and they account for 2/3 of the negative gap in the unconditional expectation of RRD between the SOEs and the NSEs.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 checks the validity of the KPSS method on our data, and applies it to estimate the Chinese patent value. Section 4 studies the effect of state ownership on R&D efficiency, and also separates and compares the impacts from the central and local SOEs. Section 6 concludes.

[2]Patents in China are categorized as invention patents, design patents and utility models. We focus on the invention patents because it is mostly related to the concept of innovation, in the sense of being the engine of technological progress. For a detailed description of these three types of patents, see Chen and Zhang (2019).

[3]To the best of our knowledge, we are among the first to apply this stock-market-based method to estimate Chinese patent value.

2 Data

We focus on the firms that were listed in the A-share market[4] as components of Shanghai (securities) composite index [5] or SZSE Component Index[6] on Jan 1st, 2020. There are 1989 such firms in total. The list of these firms is obtained from DataYes!(Uqer) database. From the same database, we extracted firms' ownership information, industrial sectors, former registered names, historical daily stock prices and daily market value. The patent data is obtained from Google Patents, which is also used by [KPSS]. We restrict our search to invention patents that were published by 2020 by the Chinese National Intellectual Property Administration, and we exclude utility model patents and design patents. This is because on average design and plant patents should add very limited value to firms [Chen and Zhang (2019)]. Firm-level R&D data is obtained from the Wind Data Service.

To collect all patents that belong to a given listed firm, we perform an automatic searching on Google Patents with firms' names. The main challenge of this step is to reduce the false positives (a patent obtained for a firm which in fact does not belong to the firm) and false negatives (a patent not obtained for a firm which in fact does belong to the firm). To overcome the false-negative challenge, inspired by [He et al], we perform two adjustments on firms' names before searching: i) we trim all symbols and punctuation marks that are not letters, characters, or numbers; ii) we remove designators of corporate form to obtain the stem names[7] [He et al] use the adjusted names (which are referred to as the "stem names" by them) for matching, which is designed to "avoid incorrectly removing any patents that may be subsequently matched to firms". Following their practice, we regard all the returned patents as potential patents that belong to the corresponding firms and then perform a selection to

[4] According to Wikipedia, A shares (Chinese: A股), also known as domestic shares (Chinese: 内资股) are "shares that are denominated in Renminbi and traded in the Shanghai and Shenzhen stock exchanges, as well as the National Equities Exchange and Quotations. These are in contrast to B shares that are denominated in foreign currency and traded in Shanghai and Shenzhen, as well as H shares, that are denominated in Hong Kong dollars and traded in the Stock Exchange of Hong Kong." A-share firms' stock price are more proper to compare efficiency accross firms' ownership, as an institutional feature of mainland China. B-share firms are dropped as the stock price volatility might incorporate changes in exchange rate, which is hard to model and capture. H-share firms are also excluded, for patents of these companies may not be registered domestically in China.

[5] The Shanghai (securities) composite index (or the SSE Composite Index) uses all listed stocks in Shanghai Stock Exchange as components.

[6] The SZSE Component Index consists of 500 selected stocks in Shenzhen Stock Exchange. They are selected to represent the market.

[7] Suffices such as "Group(集团)", "Limited-Liability(有限/责任)", "Stock(股份/持股)" and "Company(公司)" are removed. Take "上海海立(集团)股份有限公司" as an example, the stem name is "上海海立" after routine (i) and (ii).

reduce false positives.

To rule out patents matched but do not belong to the firms, we first perform an exact matching. In this paper, exact matching means that given a patent, one of the assignee(s) is exactly a listed firm[8]. We also allow a matching with firms' names without the content in the bracket, if there is any. For example, patents with an assignee being "上海海立（集团）股份有限公司"(Shanghai Highly (Group) Co., Ltd) or "上海海立股份有限公司"(Shanghai Highly Co., Ltd) will be matched to "上海海立（集团）股份有限公司"(Shanghai Highly (Group) Co., Ltd). Around 77% of the potential patents can be matched to a listed firm with this exact matching rule. The 23% left in our sample mainly fall into the following three categories: (i) patents of other companies whose names contain the stem name of a targeted listed firm[9]; (ii) patents of subsidiary firms, joint ventures, or the parent company containing the stem name of a targeted listed firm[10]; (iii) patents from subsidiary factories and R&D divisions of targeted companies[11]. While the first case should be shuffled out without doubt, the second and the third categories deserve some deliberation.

We delete the second category and keep the third. We delete subsidiary firms and joint ventures because even though events related to them may cause some volatility in the stock price of a targeted firm, we only have the pool of patents from subsidiary firms whose names contain the stem name. Keeping patents of these subsidiary firms might lead to a possible selection bias. Ideally, to include patents from subsidiary firms and joint ventures, one should collect patents of all subsidiary firms, including those subsidiaries whose names are drastically different from that of the targeted firm. However, this work is beyond the scope of this paper. Additionally, whether and by how much will actions of subsidiary firms/joint ventures affect stock price remain unclear. We also eliminate parent firms' patents because their granting actions might not be reflected in the stock price of the targeted firms. We keep the

[8]Codewise, this means two strings are equal.

[9]For example, patents with assignee "锦州东方雨虹建筑材料有限责任公司"(Jinzhou Orient Yuhong Building Materials Co., Ltd.) will be included in the patents pool of "东方集团股份有限公司"(Orient Group), as the former contains "东方"(Orient), the stem name of the latter. However, they are two different unrelated entities.

[10]For example, patents of "上海海立电器有限公司"(Shanghai Highly Electric Appliance Co., Ltd) are included for "上海海立（集团）股份有限公司"(Shanghai Highly Group Co., Ltd) but the former is a subsidiary firm of the latter. For another instance, patents of "中国石油化工集团"(China Petrochemical Corporation) will be included for "中国石油化工股份有限公司"(Sinopec) but the former is the parent company of the latter. In both cases, these patents are mistakenly included because the former companies contain the searched stem names.

[11]For instance, "深圳市中金岭南有色金属股份有限公司丹霞冶炼厂"(Shenzhen Zhongjin Lingnan Non-ferrous metal Co., Ltd., Danxia Foundry) is a subsidiary factory of "深圳市中金岭南有色金属股份有限公司"(Shenzhen Zhongjin Lingnan Non-ferrous metal Co., Ltd.)

patents from subsidiary factories and R&D divisions because it is very unlikely that a subsidiary factory/division will not be named after its firm, thus including them is unlikely to cause any selection bias. Meanwhile, as a part of a firm, actions of a subsidiary R&D division or factory should affect firms' stock price as much as the firms' actions per se.

In practice, to delete the second category and keep the third, we further extend the exact matching rule to the "left-aligned strict substring matching using firms' full name". Specifically, we keep those patents with one assignee contains the full name of the targeted firm as a substring from the left, and the leftover suffix can contain terms like "factory" and "R&D division". If the assignee contains the full name from the left but the remained suffix contains "subsidiary firm", then the patent will be dropped. In this way, around 80% of the patents are matched.

Finally, we perform a manual check to ensure the accuracy of matching[12]. The manual check ensures that the algorithm achieves the intended selection principle. Moreover, it helps to adjust the typos contained in the assignee and some uncommon/unsystematic variation of firms' names.

This dataset contains 173,789 patents[13] of 1225 listed firms, on average 142 patents per firm. For each patent, we have the application date and ID, granting date and ID, inventors and the assignee(s).

We believe this patent data is by far the best for patent-related analysis of Chinese listed firms. Our dataset differs from the published database by [Zi-Lin He, Tony W. Tong, Yuchen Zhang & Wenlong He], a database linking Chinese patents to China's census firms, on three aspects. First, we have included more matched patents per firm. Among the 2859 listed firms included in [He et al], on average each firm is matched with 25.8 patents, whereas in our dataset, each firm is on average matched to 142 patents. Second, our matching rule differs from that of [He et al]. Given a targeted firm, [He et al] does not exclude subsidiary firms or parent firms. For example, they match a patent from "TCL通讯设备(惠州)有限公司"(TCL HuiZhou Limited) to "TCL通讯设备股份有限公司"(TCL Technology), the former being a subsidiary firm of the latter. However, TCL Technology has another subsidiary firm called "新乡美乐科技"(Xinxiang Meile Technology), whose firm name does not resemble the the TCL Technology at all and is thus left out in the matching of [He et al]. In our case, patents from any subsidiary firms are intended to be dropped. For another instance, for "东风汽

[12]We check only those firms with over 50 patents assigned to avoid any possible systematic matching error that are ubiquitous enough to cause any bias. It will also reduce the burden of labor.

[13]Patents with multiple listed component firms are duplicated in this dataset.

车股份公司"(Dongfeng Automobile Co., Ltd), patents of “东风汽车有限公司/东风汽车公司"(Dongfeng Motor Corporation Ltd), its parent company, are also matched to it by [He et al]. Actually, this parent company owns more than one listed firm. As a result of any granting of patents from this parent company, it is unclear which listed sub-firms' stock prices will react, if there is any. Cases of this kind are also intended to be avoided by us. Third, due to the limited number of listed firms, we can do a more comprehensive manual check. For the three differences, we believe that our dataset is more recommended for analysis of patents of listed firms. That being said, the database provided by [he et al] should not be undervalued at all, as it incorporates unlisted firms and links patents to the ASIE database.

3 Estimation of Chinese Patent Value

3.1 Validity of the KPSS Method in Chinese Economy

Before applying the KPSS method to the estimation of Chinese patent value, we test for its validity using Chinese data, to address the concern that institutional difference between U.S. and China may render the method justified in the former unsuitable for the latter. To do so, we regress the intraday volatility of stock price on the indicator of patent issuance.

We define the intraday volatility of a stock as the percentage change from the lowest to the highest price in a trading day[14], and denote it by v_{fd}, where f and d are the firm and day indices. The patent issuance indicator, I_{fd}, is a dummy variable taking value one if and only if there is at least one new patent granted to firm f on day d. In the following specification

$$v_{fd} = \alpha + \sum_{l=-1}^{3} \beta_l I_{fd+l} + \lambda Z_{fd} + u_{fd}, \tag{1}$$

the estimates $\{b_{-1}, \cdots, b_3\}$ captures the dynamic impact of the news of patent issuance on the intraday volatility in a week. The control variable set Z includes the firm-year fixed effects, day of week, and the one-day lag of intraday volatility. The figure below reports the estimated coefficients, together with the 90% confidence intervals (standard errors clustered at the firm-year level).

[14]In the KPSS method, the daily turnover rate, rather than intraday price volatility, is used. However, as the authors recognized, “prices can adjust to new information absent any trading”.

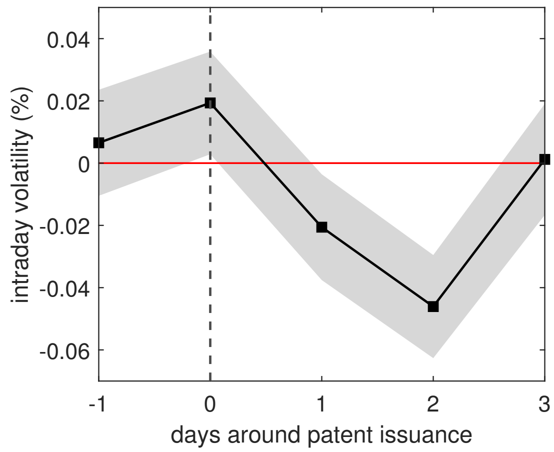

Figure 1: Intraday Volatility of Stock Price during Patent Issuance Weeks

In Figure 1, the black squares denote estimated coefficients $\{\beta_{-1}, \cdots, \beta_3\}$, and the grey area the 90% confidence interval. Being on one day prior to the patent issuance has no significant impact on the intraday volatility, a good feature without pretrend. At the day of patent issuance, there is an increase in intraday volatility of stock price, by 0.02%. Although the magnitude is mild compared to the median of intraday volatility, 3.26%, the significantly higher volatility reflects that the Chinese stock market responds to new information from patent issuance. The two days' drop in intraday volatility following the patent issuance, before reverting to zero, may suggest that the market has less disagreement on a firm's value when information from a new patent is absorbed.

With the above observations, we conclude that on Chinese stock market, the adjustment to news conveyed by a new patent happens and completes within the day on which the patent is issued. It thus validates the application of the KPSS method to evaluate Chinese patents, only that with a recalibrated time window of one day during which the stock market responds to the patent issuance.

3.2 Application of the KPSS Method to Chinese Patents

In this subsection, we apply the KPSS method to estimate the economic value of invention patents granted to Chinese publicly listed firms. To see why this method is chosen over others to construct our database of patent value, we start with a brief literature review of the methodology used to evaluate firm innovation.

The most straightforward way to quantify a firm's innovation performance is to tally its patents, either applied or granted, with a fixed period of time. This is well documented in Griliches (1984), and its problem in not distinguishing the intrinsic variability of patent value is already mentioned in Griliches (1990). The primitive method of patent counting has been modified by weighting by citations (Lanjouw and Schankerman (2004), Hall, Jaffe and Trajtenberg (2005), Celik and Tian (2020)), as more valuable patents should get cited more frequently; by using the patent renewal data as approxy (Schankerman and Pakes (1986), Pakes (1986), Bessen (2008)), under the argument that the cost a firm bears to renew a patent reflects its value; and also by looking at the dynamic pattern of citations (Gay et al. (2005), Marco (2007)), because patents with higher value should be discovered and cited faster.

All these modifications to patent counting rely on their respective assumptions regarding firm behavior, and none of them is as solid as the efficient market hypothesis (EMH). The EMH implies that all events that may change firm value – such as the issuance of new patents – will be immediately noticed by the investors on the stock market and lead to adjustment of the market value of the associated listed firms. Researches in this spirit include Pakes (1985), Austin (1993), Hall, Jaffe and Trajtenberg (2005), Nicholas (2008), and Kogan et al. (2017). They propose a variety of arts and sciences in extracting the value of patents from stock price flucutation, among which the KPSS method displays a prominent delicacy separating the signal from the noise. In the following, we provide a minimal introduction of the KPSS approach, to show how we apply it to the evaluation of Chinese patents. More details are to be found, of course, in their paper.

As in the KPSS method, the stock return R is decomposed into the value of patent j, v_j, and the factor unrelated to the patent, ε_j:

$$R_j = v_j + \varepsilon_j. \tag{2}$$

In Section 3.1, the time window for Chinese stock market to respond to the patent issuance is one day. Thus R_j here is the daily stock return, calculated as the daily growth rate of the closing price.

The patent value component v_j is not observable, but can be inferred from the observation of R_j. Under the assumption that the patent value component follows a truncated normal distribution: $v_j \sim \mathcal{N}^+(0, \sigma^2_{vft})$[15], and that the non-patent component is normally distributed:

[15]Subscripts f and t indicate the firm and time to which and when patent j is issued.

$\varepsilon_j \sim \mathcal{N}(0, \sigma^2_{\varepsilon ft})$, the expected patent value conditional on R_j is

$$\mathbb{E}[v_j|R_j] = \delta_{ft} R_j + \sqrt{\delta_{ft}} \sigma_{\varepsilon ft} \frac{\phi\left(-\sqrt{\delta_{ft}} \frac{R_j}{\sigma_{\varepsilon ft}}\right)}{1 - \Phi\left(-\sqrt{\delta_{ft}} \frac{R_j}{\sigma_{\varepsilon ft}}\right)}, \tag{3}$$

where ϕ and Φ are the pdf and cdf of the standard normal distribution, and δ is the signal-to-noise ratio:

$$\delta_{ft} = \frac{\sigma^2_{vft}}{\sigma^2_{vft} + \sigma^2_{\varepsilon ft}}. \tag{4}$$

In the KPSS method, σ^2_{vft} and $\sigma^2_{\varepsilon ft}$ can vary across firms and years. However, the signal-to-noise ratio, δ, is assumed to be a constant[16], and estimated with the following regression:

$$\log(R^2_{fd}) = \gamma I_{fd} + \lambda Z_{fd} + u_{fd}, \tag{5}$$

where the set of control variables Z_{fd} includes the firm-year fixed effects and day of week. The coefficient estimate on patent issuance dummy I_{fd} is $\widehat{\gamma} = 0.0144$. The recovered estimate of the signal-to-noise ratio is thus $\widehat{\delta} = 1 - e^{-\widehat{\gamma}} \approx 0.0143$. This is quite close to the signal-to-noise ratio estimated in the KPSS paper, which is 0.0145. We interpret this numerical similarity as evidence of the institutional resemblance between the Chinese and U.S. stock markets in the ways they respond to the patent issuance to their respective listed firms.

The last step before which equation (3) can be put to use is to estimate the variance $\sigma^2_{\varepsilon ft}$. Following the KPSS approach, we firstly compute the mean of the squared daily stock returns in the firm-year level, $\widehat{\sigma}_{ft}$. Secondly, we calculate the fraction of trading days with patent announcements, d_{ft}. Finally, we recover the variance of the measurement error through $\widehat{\sigma}^2_{\varepsilon ft} = \widehat{\sigma}^2_{ft}\left(1 + d_{ft}(e^{\widehat{\gamma}} - 1)\right)^{-1}$[17].

The conditional expectation of the rate of return from patent, $\mathbb{E}[v_j|R_j]$, multiplied by the firm's market capitalization (market value of all outstanding shares), yields the change

[16] The argument provided by the authors is that if this constraint is relaxed, both variances can vary arbitrarily at firm-year level, and the number of parameters becomes very large and infeasible to estimate. Another more intuitive justification can be that the constant signal-to-noise ratio summarizes the time-invariant institutional factors of the stock market, whose influence is homogeneous over all listed firms.

[17] We also estimate $\sigma^2_{\varepsilon ft}$ with an alternative method, by taking the mean of squared daily stock returns on all trading days without patent announcements. It gives an estimate very close to the one we use in the paper – the percentage deviation between the two has a mean of 0.1251 and a standard deviation of 2.3123.

in firm value due to patent issuance. It needs to be adjusted in the following two aspects to serve as a proper measure of patent value: (1) if there are more than one patents granted to the same firm in one day, each of them is considered to have the same value; (2) if the market's subjective probability of the success in a patent application is high, its response on the announcement day will underestimate the value of the patent, because by then a large portion of such news has already been absorbed. Taking these two issues into account, the economic value of patent j is

$$\xi_j = (1 - \overline{\pi}_j)^{-1} \frac{1}{N_j} \mathbb{E}[v_j | R_j] M_j, \tag{6}$$

where M_j is the market capitalization of the firm who owns patent j, on the trading day prior to its issuance. N_j denotes the number of patents granted to the same firm at the same day. The subjective probability of successful application is approximated by the annual frequency of patent granted over all applications[18], $\overline{\pi}_j$, whose time path is plotted below.

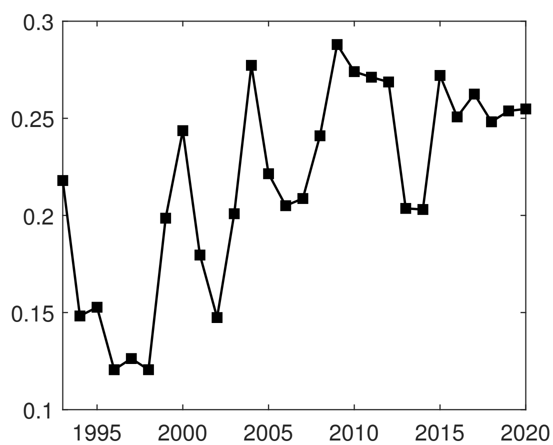

Figure 2: Frequency of successful invention patent applications (1993-2020)

The data is available at China National intellectual Property Administration (https://www.cnipa.gov.cn/). The time series starts with the year 1993 because it is the earliest year in which a patent is granted to a listed firm in our sample. As of this paper is written, the observation of 2020 is unavailable, so we calculate it as the moving average of the preceding three years.

By applying the KPSS method introduced above, we estimate the value of invention patents matched to Chinese listed firms in our sample. The summary statistics of the patent

[18] In Kogan et al. (2017), this probability is a constant over all years.

value ξ, normalized to 2006 million RMB using CPI[19], are reported in the following table:

Table 1: Descriptive Statistics of Patent Value

	$R(\%)$	$\mathbb{E}[v\|R](\%)$	ξ
Mean	-0.01	0.27	48.70
Std. dev.	3.28	0.11	181.00
Percentiles			
p1	-9.75	0.09	0.49
p5	-4.58	0.13	1.05
p10	-3.09	0.16	2.07
p25	-1.33	0.20	5.98
p50	0	0.24	14.63
p75	1.36	0.32	34.81
p90	3.16	0.42	86.87
p95	4.68	0.49	165.84
p99	9.52	0.63	635.51
Obs.	3, 316, 318	103, 301	145, 608

Notes: Statistics of daily stock return R and conditional expectation of return of patent $\mathbb{E}[v|R]$ are obtained using daily stock market data from December 19, 1990 to August 28, 2020. Those of patent value ξ are calculated at the patent level, with application date from July 9, 1992 to July 24, 2020 (the granting date ranges from October 27, 1993 to August 28, 2020).

In Table 1, the percentiles of the conditional expectation of the patent value component of stock returns, $\mathbb{E}[v|R]$, highly resemble those documented in Kogan et al. (2017). We see this as further evidence of the similarity in the magnitudes by which Chinese and U.S. stock markets respond to patents granted to their respective firms.

3.3 Firm-year Patent Value of SOEs and NSEs

We aggregate the estimated patent value to firm-year level by the date of patent application. One can also use the date of patent issuance instead, as done in the KPSS method. The reason for our choice is that we care about R&D efficiency in later sections of this paper, which requires us to match the timing of R&D output with that of their corresponding input as well as possible. Aggregating by the date of patent issuance incurs the problem that

[19] In the year 2006, The Ministry of Finance of the People's Republic of China issued "Accounting Standards for Enterprises No.6 – Intangible Assets", in which it is regulated by provision 25th that enterprises should reveal the total R&D expenditure recognized as expenses at current period.

patents issued in the same year may be applied in different years, causing the difficulty in assigning them as the output of the same year's R&D expenditure.

Following the notation in the KPSS method, we denote the aggregated patent value applied by firm f in year t by Θ_{ft}, defined as

$$\Theta_{ft} = \sum_{j \in P_{ft}} \xi_j, \tag{7}$$

where P_{ft} is the index set of all patents applied by firm f in year t. The patent value ξ_j here is again normalized to 2006 million RMB. To control for the variation in firm size, we also scale the firm-year patent value by firm-year revenue, Rev_{ft}, and denote the scaled patent value by θ_{ft}:

$$\theta_{ft} = \frac{\Theta_{ft}}{Rev_{ft}}. \tag{8}$$

The table below summarizes the descriptive statistics of the firm-year patent value, both in level and scaled. We also distinguish them across state-owned and non-state-owned firms.

Table 2: Descriptive Statistics of Firm-year Patent Value

	Non-scaled (2006 million RMB)			Scaled (%)		
	Θ	Θ^{SOE}	Θ^{NSE}	θ	θ^{SOE}	θ^{NSE}
Mean	1065.26	1638.16	609.35	15.77	10.36	19.50
Std. dev.	6414.45	8934.88	3146.82	44.24	36.42	48.56
Percentiles						
p1	3.17	3.31	2.77	0.07	0.05	0.11
p5	7.09	7.72	6.84	0.27	0.17	0.48
p10	11.16	12.04	10.51	0.51	0.30	0.80
p25	26.68	30.47	24.99	1.37	0.85	2.08
p50	85.11	103.38	74.92	4.18	2.52	5.85
p75	309.00	428.74	254.26	12.68	7.60	16.62
p90	1167.66	1760.50	804.23	33.80	22.68	41.79
p95	2676.29	4354.51	1837.80	63.91	41.44	77.92
p99	24895.05	33203.31	10495.59	207.43	126.61	266.22
Obs.	6,657	2,950	3,707	5,383	2,197	3,186

Notes: Variables with superscript SOE refer to those from State-owned firms, and superscript NSE is for non-state-owned firms. The database includes 3,772 Chinese listed firms and ranges from 1992 to 2020 (the time range of scaled firm-year patent value is 2006 to 2019).

If we regard the patent value of SOEs and NSEs reported above as random draws from independent distribution $F_{\Theta^{\text{SOE}}}$ and $F_{\Theta^{\text{NSE}}}$, then from Table 2, it appears that $F_{\Theta^{\text{SOE}}}$ first-order stochastically dominates $F_{\Theta^{\text{NSE}}}$; if we consider the scaled patent value, however, it seems that $F_{\theta^{\text{NSE}}}$ first-order stochastically dominates $F_{\theta^{\text{SOE}}}$. This observation is accompanied by a pair of t-tests on the difference in the first moments across the two groups of SOEs and NSEs:

Table 3: Two-sample t-test with Unequal Variances

Group	Obs.	Mean	Std. Err.	95% Conf. Interval
Unscaled firm-year patent value (2006 million RMB)				
Non-state-owned (Θ^{NSE})	3,707	815.15	69.12	[679.63, 950.67]
State-owned (Θ^{SOE})	2,950	2096.24	203.54	[1697.14, 2495.33]
mean(Θ^{NSE}) − mean(Θ^{SOE})		−1281.08	98.37	[−1702.53, −859.64]
Scaled firm-year patent value (%)				
Non-state-owned (θ^{NSE})	3,186	19.50	0.86	[17.82, 21.19]
State-owned (θ^{SOE})	2,197	10.36	0.78	[8.84, 11.89]
mean(θ^{NSE}) − mean(θ^{SOE})		9.14	1.16	[6.87, 11.41]

From Table 3, it is clear that the average patent value of SOEs is significantly higher than that of NSEs, suggesting the SOEs are creating greater economic value through innovation. However, this is mainly due to the larger sizes of the SOEs, as the opposite is true when the scaled patent value is instead in concern. Does it imply that the SOEs are less efficient in R&D activities? The next section aims to provide an answer.

4 State Ownership and R&D Efficiency

4.1 Measures of R&D Efficiency

To study the efficiency, or the rate of return to R&D (RRD), both the input and output of firm R&D activity need to be properly defined. For the input, we use the firm-year R&D expenditure (RDE), disclosed in the Income Statement by Chinese listed firms since 2006. The output of R&D is approximated by forward innovation value (Θ), which is the aggregate patent value at the firm-year level by the year of application, as in equation (7).

Due to the lack of information needed for matching R&D expenditure to the exact patents, we use two defitions of the RRD, with different gaps between the time of R&D expenditure iccured, and that of the patent applied: the one-year forward

$$RRD_{ft}^{\text{F1}} = \frac{\Theta_{ft+1}}{RDE_{ft}}, \tag{9}$$

and the three-year forward moving average

$$RRD_{ft}^{\text{MA3}} = \frac{\left(\sum_{i=1}^{3} \Theta_{ft+i}\right)/3}{RDE_{ft}}. \tag{10}$$

4.2 Control for Returns to Scale of R&D

As we contrast the R&D performance by the SOEs with that by the NSEs, the firm-level R&D intensity (R&D expenditure divided by revenue) must be taken into consideration. For example, if R&D activity has decreasing returns to scale, and if for whatever reasons the SOEs incline to exert more effort on R&D, then the simple observation that the SOEs exhibit lower returns to R&D on average can serve as no evidence that they suffer from R&D inefficiency. Instead, it cannot be rejected that the lower RRD of the SOEs is no more than a mechanical outcome of the decreasing returns to scale of R&D, reflecting no defects in the SOEs' capacity to conduct research and development projects.

The above is the concern under which we put the return of R&D and R&D intensity to the same picture. For a first look, we draw the binned scatterplots with the RRD as the dependent variable, and RDI the independent variable, for the two RRD measures with different time horizons. The binned scatterplot is a non-parametric way to visualize the pattern of the expectation of the independent variable conditional on the chosen dependent variable. It groups the independent variable into equal-sized bins, and computes the mean of the independent and dependent variables within each bin, then generates a scatterplot of these data points[20].

[20]For the details of the algorithm we use, see Stepner (2013); for a survey of the general use of Binscatter in applied microeconomics, see Cattaneo et al. (2019).

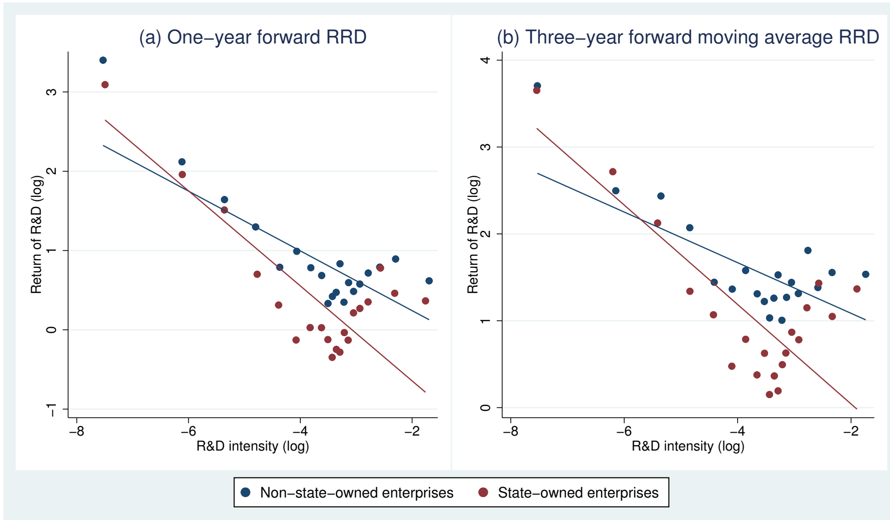

Figure 3: Binned Scatterplots of Returns to R&D from SOEs and NSEs

From Figure 3, it is evident that for almost any R&D intensity, the conditional expectation of returns to R&D from the state-owned firms is lower than that from the non-state-owned ones. This pattern, however, may still be contaminated by the impact from other variables. To address this concern, we create another set of binned scatterplots, where we control for year fixed effect, industry fixed effect, revenue, one-year lag of RRD and firm-year number of patents applied[21].

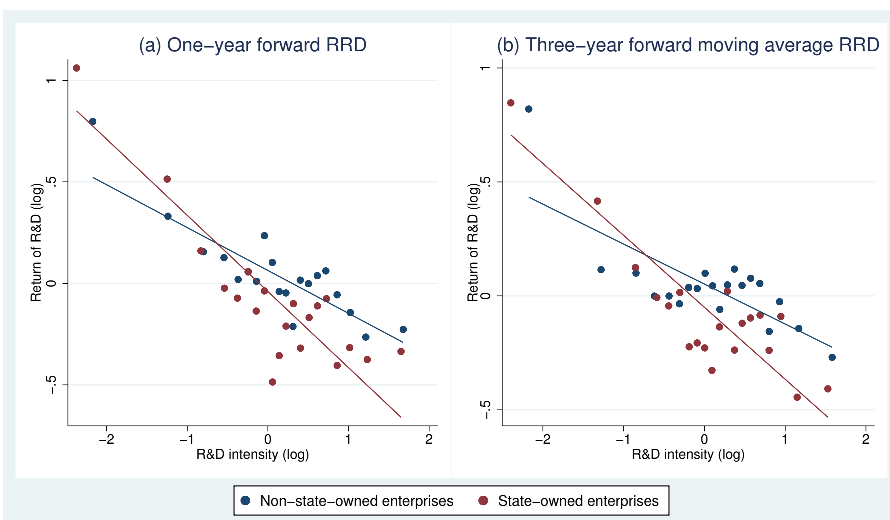

Figure 4: Binned Scatterplots of Returns to R&D from SOEs and NSEs, with Controls

[21]By the number of patents applied, we actually refer to the number of patents applied and finally granted. This is because our data only covers the granted patents. This abuse of term is carried over the rest of this paper.

Either panel in Figure 4 is generated as follows: firstly, the algorithm run two regressions of the RRD and RDI on the set of the aforementioned control variables, respectively; secondly, obtain the residualized RRD and RDI where the impact from the chosen controls are removed; finally, plot the binned scatterplots using the same fashion as with Figure 3, but using the residualized RRD and RDI[22].

The message from Figure 4 is otherwise identical to that from Figure 3, except for that with very low RDI, the SOEs have higher conditional expectation of RRD. This difference is tiny, as it accounts for a small fraction of the observations[23].

Although these two sets of graphs are illustrative in suggesting the SOEs have lower rate of return to R&D conditional on R&D intensity, it is not informative on how significant this difference may be. We continue with our inquiry employing reduced-form estimation of the impact of state ownership on returns to R&D.

4.3 Baseline Estimation

We use the following specification to estimate the impact of state ownership on returns to R&D. The data is described in Section 2.

$$\log\left(RRD_{ft}\right) = \alpha + \eta_{ft} + \beta_0 State_f + \beta_1 State_f \times \log\left(RDI_{ft}\right) + \beta_2 \log\left(RDI_{ft}\right) + \lambda Z_{ft} + u_{ft} \quad (11)$$

In the above, η is the industry-year fixed effect[24]. The variable $State$ is a dummy indicating whether a firm is state-owned. The set of control variables is denoted by Z_{ft}, and includes the one-year lag of dependent variable, firm-year revenue (in log), and the firm-year number of patents applied (in hundreds).

By including R&D intensity (in log) in the regression, we control for the returns to scale of R&D, while we leave the data to determine whether the returns to scale is decreasing, constant or increasing. Furthermore, by interacting the RDI with state-ownership indicator, we allow such returns to scale of SOEs to be different from those of the NSEs, either quantita-

[22]This procedure is justified by the Frisch–Waugh–Lovell theorem.

[23]The 10th percntile of the residualized log RDI with one-year forward RRD is -1.09, and that with three-year forward moving average RRD is -1.06.

[24]We use the seven-digit first level industry classification, provided by DataYes, for the industry dummy. It records the updating history of listed firms' industry classification, thus allowing for firm-year level variation. Partly due to the fact that different classification standards became available at different times, the industry classification database uses a mixture of five standards: China Securities Regulatory Commission (2012 version), CITIC, Hang Seng, China Securities Index and Shenyin & Wanguo Securities.

tively or qualitatively. An alternative interpretation, with more economic intuition, is that the coefficient on the interaction term, β_1, captures the impact of state ownership on the conditional expectation of RRD for given RDI. On the other hand, the coefficient on the indicator *State* reflect the impact of state ownership on the unconditional expectation of RRD.

For robustness, we use the two measures for RRD defined by equations (9) and (10), respectively. We also run regressions with and without the set of control variables Z in (11). The estimation results are reported in the table below.

Table 4: Estimation of the impact of state ownership on returns to R&D

	One-year forward RRD		Three-year MA RRD	
	(1)	(2)	(3)	(4)
Key variables				
State	-1.102^{***}	-0.611^{***}	-1.454^{***}	-0.346^{*}
	(0.150)	(0.138)	(0.225)	(0.177)
State by RDI	-0.182^{***}	-0.125^{***}	-0.273^{***}	-0.056
	(0.037)	(0.037)	(0.054)	(0.046)
RDI	-0.401^{***}	-0.219^{***}	-0.305^{***}	-0.208^{***}
	(0.034)	(0.030)	(0.051)	(0.031)
Controls				
Lag RRD		0.616^{***}		0.765^{***}
		(0.025)		(0.044)
Firm size		-0.117^{***}		-0.118^{***}
		(0.020)		(0.031)
Patents applied		0.045^{***}		0.029^{***}
		(0.009)		(0.010)
Constant	-0.104	-1.683^{***}	0.162	-3.155^{***}
	(0.134)	(0.221)	(0.202)	(0.435)
R-squared	0.430	0.693	0.447	0.838
Observations	5,058	3,439	2,599	1,903

Note: *, ** and *** Indicate significance at 10%, 5% and 1%, respectively. Standard errors clustered at the firm-year level are in parentheses. State refers to the dummy variable indicating whether a firm is state-owned. Firm size is approximated by revenue. The patent number applied is in hundreds.

For all the four specifications in Table 4, the impact of state ownership on the returns to scale of R&D, as captured by the second and third rows, is estimated to be negative and siginificant (except for the last column). Quantitatively, it means that on average, an increase in RDI by one percent is associated with an additional deline in RRD by 6 to 27 percent for the SOEs. The first row of the table shows that the impact of state ownership on the unconditional expectation of returns to R&D is also negative and significant across all four specifications. Its magnitude accounts for 21% to 90% of the standard deviation of pooled RRD. The combined effects imply that the returns to R&D is higher for SOEs with very low RDI, and the reverse is true with larger RDI. In fact, the first quartile of the log RDI in our full sample is -4.230, above which the linear model (11) predicts better R&D performance by the non-state-owned firms. This is consistent with the message from the binned scatterplots in Section 4.2.

The evidence above suggests that the state ownership in general plays a significantly negative role in firms' R&D performance measured by the RRD, except for those with so low R&D intensity that they account for only a small fraction of all firms.

The estimated coefficients on other variables are in agreement with common observation. For example, the third row indicates a decreasing returns to scale of R&D activity; the coefficient on the lag RRD suggests that the series is autoregressive; the row below it displays a negative correlation between firm size and returns to R&D; the last control reports that patent applied is positively associated with RRD, but by quite low magnitude.

4.4 Central and Local SOEs: Are Their R&D Efficiency Different?

Under the general appellation of "State-owned enterprises", there are different categories reflecting more subtle difference in the nature of ownership. In China, the central SOEs (CSOEs) refer to the enterprises funded and managed by the Central People's Government, or by the State-owned Assets Supervision and Administration Commission (SASAC) of the State Council. The local SOEs (LSOEs), on the other hand, are those owned by local goverment, and under the supervision of the local SASAC. This subsection studies whether there is heterogeneity in the impacts on the central and local SOEs on firms' returns to R&D[25].

To distinguish the influence of CSOEs and LSOEs on firm returns to R&D, we use the following specification modified from (11):

$$\begin{aligned}\log\left(RRD_{ft}\right) =& \alpha + \eta_{ft} + \beta_{C,0} CSOE_f + \beta_{L,0} LSOE_f + \beta_{C,1} CSOE_f \times \log\left(RDI_{ft}\right) \\ &+ \beta_{L,1} LSOE_f \times \log\left(RDI_{ft}\right) + \beta_2 \log\left(RDI_{ft}\right) + \lambda Z_{ft} + u_{ft},\end{aligned} \tag{12}$$

where decompose the *State* indicator in the baseline regression (11) into two dummies of the central and local SOEs; the other variables have the same meanings. The above regression

[25]There is another category: state-holding enterprises. However, this accounts for a very small fraction in our data, only 11 out of the 5,058 observations, we thus neglect it from this study.

simultaneously identifies the effect of being CSOE or LSOE relative to NSE. To further explore the difference in R&D efficiency between these two types given a firm is an SOE, we run the below regression over the subsample of all SOEs:

$$\log\left(RRD_{ft}\right) = \alpha + \eta_{ft} + \beta_{c,0} CSOE_f + \beta_{c,1} CSOE_f \times \log\left(RDI_{ft}\right) + \beta_2 \log\left(RDI_{ft}\right) + \lambda Z_{ft} + u_{ft}. \tag{13}$$

The estimation results from regressions (12) and (13) are reported in Table 5. Columns (1), (2), (5) and (6) record the results from specification (12). From the first two rows, it is clear that both the central and local SOEs exhibit lower unconditional expectation of the returns to R&D than the NSEs. However, the magnitude of such gap in RRD from the CSOEs is only about 1/3 of that from the LSOEs, and is less significant, especially when control variables are included. The third and fourth rows of the same columns show that, the CSOEs' returns to scale of R&D is not significantly different from that of the NSEs (except for the fifth specification); while the LSOEs have significantly lower returns to scale than the NSEs. Therefore, we infer from the above results that for all the RDI with which the central SOEs are less efficient in R&D than the NSEs, the local SOEs' R&D efficiency must be even lower. For smaller RDI, however, the local SOEs dominate the other two types in R&D efficiency.

As we restrict the regression to the subsample of the SOEs, we find again that the unconditional expectations of RRD is higher for the central SOEs, and so is the returns to scale of RDI. This is shown by columns (3), (4), (7) and (8) of Table 5. Almost all of these results are significant. For firms with high RDI (closer to one), the RRD from the CSOEs can be as high as 1.3 times of that from the LSOEs. For the RDI below the first quartile among all SOEs (the corresponding log RDI is -5.709), it is the LSOEs who have higher returns to R&D.

In summary, the comparison in R&D efficiency between the central and local SOEs depends on the R&D intensity: the central SOEs have better R&D performance for most of the range of RDI (above the first quartile). This is because of their smaller degree of declining returns to scale of R&D, as well as of the institutional factors not captured by the R&D intensity and other covariates, such as the firm size or R&D performance in the past.

Table 5: Estimation of the impact of central and local state ownership on returns to R&D

	One-year forward RRD				Three-year forward moving average RRD			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Key variables								
CSOE	-0.489^{**}	-0.313^{*}	1.103^{***}	0.714^{***}	-0.782^{***}	-0.198	1.264^{***}	0.530^{**}
	(0.193)	(0.170)	(0.277)	(0.208)	(0.268)	(0.189)	(0.303)	(0.247)
LSOE	-1.799^{***}	-1.022^{***}			-2.320^{***}	-0.626^{**}		
	(0.186)	(0.172)			(0.233)	(0.262)		
CSOE by RDI	-0.070	-0.075	0.201^{***}	0.130^{**}	-0.154^{**}	-0.040	0.225^{***}	0.084
	(0.053)	(0.050)	(0.066)	(0.055)	(0.073)	(0.058)	(0.073)	(0.055)
LSOE by RDI	-0.302^{***}	-0.195^{***}			-0.419^{***}	-0.097^{*}		
	(0.042)	(0.043)			(0.053)	(0.056)		
RDI	-0.394^{***}	-0.216^{***}	-0.735^{***}	-0.455^{***}	-0.302^{***}	-0.208^{***}	-0.737^{***}	-0.376^{***}
	(0.033)	(0.030)	(0.033)	(0.040)	(0.050)	(0.031)	(0.037)	(0.072)
Controls								
Lag RRD		0.608^{***}		0.585^{***}		0.758^{***}		0.679^{***}
		(0.025)		(0.037)		(0.045)		(0.071)
Firm size		-0.116^{***}		-0.120^{***}		-0.118^{***}		-0.121^{***}
		(0.020)		(0.030)		(0.030)		(0.044)
Patents applied		0.049^{***}		0.063^{***}		0.030^{***}		0.040^{*}
		(0.010)		(0.018)		(0.010)		(0.022)
Constant	-0.078	-1.635^{***}	-2.101^{***}	-2.376^{***}	0.176	-3.118^{***}	-2.163^{***}	-0.681^{**}
	(0.133)	(0.226)	(0.202)	(0.323)	(0.200)	(0.437)	(0.189)	(0.303)
Sample	All	All	SOEs	SOEs	All	All	SOEs	SOEs
R-squared	0.440	0.696	0.549	0.751	0.461	0.839	0.575	0.831
Observations	5,047	3,432	2,008	1,445	2,593	1,899	1,146	878

Note: *, ** and *** Indicate significance at 10%, 5% and 1%, respectively. Standard errors clustered at the firm-year level are in parentheses. State refers to the dummy variable indicating whether a firm is state-owned. Firm size is approximated by revenue. The patent number applied is in hundreds. The 36 observations of state owned firms which are neither central nor local SOEs are excluded from this estimation.

4.5 State Ownership and R&D Efficiency: Non-linear Estimations

Though the results from the previous sections are significant and robust, they are subject to two limitations: firstly, the parametric models (11) and (13) assumes a linear relationship between the RDI and the R&D efficiency of central or local SOEs; secondly, the RDI from different industries may not be comparable: some RDI in one industry that is considered high may be low in another. To get rid of these limitations, this section revisits the question of the R&D efficiency of the central and local SOEs with a non-linear, semi-parametric model.

We construct a R&D intensity measure that is comparable across industry-year cells. For each of such cells, we divide the within-cell range of log RDI into ten decile groups, and generate a set of dummies $\{D_{s,ft}\}_{s=1}^{10}$ to indicate to which decile group a firm belongs. For example, if $D_{3,ft} = 1$, firm f's log RDI lies between the second and third deciles of the distribution of log RDI from all firms from the same industry and year. These decile-group dummies thus serve as an ordinal scale that ranks the RDI of firms from different industries and years. We use the group dummies in the following way:

$$\log\left(RRD_{ft}\right) = \alpha + \eta_{ft} + \sum_{s=1}^{10} \beta_{S,s} SOE_f \times D_{s,ft} + \sum_{s=1}^{10} \beta_s \times D_{s,ft} + u_{ft}, \tag{14}$$

$$\log\left(RRD_{ft}\right) = \alpha + \eta_{ft} + \sum_{s=1}^{10} \beta_{C,s} CSOE_f \times D_{s,ft} + \sum_{s=1}^{10} \beta_{L,s} LSOE_f \times D_{s,ft} + \sum_{s=1}^{10} \beta_s \times D_{s,ft} + u_{ft}, \tag{15}$$

where η_{ft} is the industry-year fixed effect. Coefficients $\{\beta_{S,s}\}_{s=1}^{10}$ capture the difference in the returns to R&D between the state-owned and the non-state-owned firms, conditional on that they are from the same decile group of R&D intensity. Similarly, $\{\beta_{C,s}\}_{s=1}^{10}$ ($\{\beta_{L,s}\}_{s=1}^{10}$) reflect the difference between the central (local) SOEs and the NSEs. Like before, we use two measures of the RRD. The estimated values of $\{\beta_{S,s}\}$ and are plotted in the figure below.

5 Concluding Remarks

We use the novel method proposed by Kogan et al. (2017) to measure the economic value of patents granted to the Chinese listed firms included in the Shanghai Composite Index or SZSE Component Index. We then estimate the impact of state ownership of firms' R&D efficiency, which is measured by the future firm-year patent value divided by current R&D expenditure. We find that the decreasing returns to scale of R&D is more prominent in state-owned firms by 6 to 27 percent; and while such heterogeneity in returns to scale is controlled, the unconditional expectation of R&D efficiency for state-owned firms is lower than that of the non-state-owned firms by 21% to 90% of the standard deviation. These two effects together mean that the role of state ownership in R&D performance depends on the R&D intensity: for firms with very low RDI, the SOEs exhibit higher R&D efficiency; for firms with medium and high RDI, the SOEs are less R&D efficient. This pattern and its magnitude are due to the local, rather than the central, SOEs.

Throughout this paper, we have used the returns to R&D as a proxy of R&D efficiency. However, the difference in this measure may not fully reflect that in the capacity to conduct R&D projects across the SOEs and NSEs. There may be some institutional motives for the SOEs to adopt those R&D projects with lower private value to the firms, but with higher positive externalities. Our data cannot answer by how much the observed gap in R&D efficiency between these types of firms is explained by their different preferences over R&D projects. We think, nevertheless, that it is a topic worthy of further studies.

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