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# Ownership and Innovation Efficiency Revisited: From Labor and Finance Perspectives

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## Abstract

The innovation efficiency of enterprises has always been an important subject of concern. The characteristics of ownership in China are distinct, and the performance of innovation efficiency of enterprises under different kinds of ownership has been discussed. Based on the different input factors, innovation efficiency is innovatively decomposed into three categories: capital input, labor input and comprehensive input. We use the data of listed companies from 2015 to 2021 to compare the three categories of innovation efficiency of state-owned enterprises and non-state-owned enterprises. We find that in terms of labor, capital, and comprehensive input innovation efficiency, as well as labor input innovation efficiency in particular, state-owned enterprises trail below non-state-owned enterprises in all three categories. Further research shows that for high-tech industry, corporate size and industry type also have an impact on the efficiency of innovation activities. Equity and tax incentives can explain the effect of privately owned ownership on the efficiency of labor and capital innovation, respectively, the principle of which lies in how to make use of the advantages of state-owned property and how to avoid the pain points of state-owned property.

## Key words

Innovation efficiency; Ownership; R&D expenses; Human capital

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## 1. Introduction

Technological innovation significantly drives economic growth (Romer, 1990) and shapes corporate strategy (Butler, 1988), with effective management being a crucial factor in the innovation process (Vangelis, 2002). In China, state-owned enterprises (SOEs) constitute the backbone of the Chinese economy, commanding a leading position in strategic domains and vital economic sectors. SOEs must be held accountable for utilizing innovation as a means of promoting economic growth. Can SOEs, however, actually succeed in this? Does the ownership type have a significant impact on innovation efficiency? Whether ownership plays a positive or inhibitory role is still debatable. Most of the research supports that in addition to enjoying many policy conveniences and preferential financing, SOEs are also subject to more policy burdens and social responsibilities compared with non-state-owned enterprises (NSOEs). State-owned attributes are a double-edged sword, affecting all aspects of the business development of enterprises. The focus of the discussion is whether, is state ownership an advantage or a burden for businesses in the distinct institutional context of China. Someone argued that SOEs have more resources, channels, and closer relationships with the government that other companies cannot match (Cumming *et al*., 2016), and it is not easy for them to believe that these "advantages" will only become a rope that restrains the innovation without bringing any benefits (Cao *et al*., 2020). However, more studies verified that when the property rights of enterprises belong to the government, the agent's motivation to innovate will be greatly weakened (Hart *et al*., 1997), significantly lagging behind NSOEs (Shleifer, 1998), which is rooted in the principal-agent problem caused by the separation of ownership and control rights. The principal-agent chain of China's SOEs is long and complex (Zhang, 1997), failing the incentive and restraint mechanism between the principal and the agent. In particular, we must consider that innovation is more of a long-term benefit project than a short-term vested interest. Still, the risks and possible losses in the process only occur in the current period. The operators of SOEs are only appointed as managers for a while, they may not enjoy the profits of innovative activities (Ling *et al*., 2008). Ultimately, the decision-making rights and profit rights of innovative activities cannot be matched (Wu, 2012), resulting in the loss of innovation efficiency of state-owned enterprises. In addition to the principal-agent problem, the policy burden faced by SOEs is also the reason for the low efficiency of innovation (Lin *et al*., 1998), which means that SOEs realize profits and play some social roles, such as ensuring employment, assuming social and public responsibilities, etc. Thus, SOEs have to invest additional human and financial resources in extra areas, leading to offsetting innovative efficiency (Bai *et al*., 2000). Furthermore, the inefficiencies that are typically linked to public ownership and management can be eliminated when state-owned businesses are transferred to private ownership (Arocena and Oliveros, 2012).

Only straightforward numerical comparisons of measured innovation efficiencies are offered by current studies of innovation efficiency losses in SOEs, calculated by outputs/inputs. Outputs typically consist of the number of innovation patents held by the firm, while inputs are generally categorized into two groups: human resources and financial resources (Shin *et al*., 2022), such as R&D workers and R&D expenses. Each input and output element are crucial to a firm's innovation efficiency. To highlight the importance of different elements, several articles have differentiated among various output types—such as patents, research grants, and journal articles—and calculated innovation efficiency under different output orientations (Chen *et al*., 2011). In existing literature, innovation efficiency is seldom analyzed based on input types, however. In fact, distortions in the pricing of labor and capital factors can hinder the attainment of an optimal resource allocation, adhering to the principle of efficiency. The rent-seeking practices of SOEs exacerbate the misallocation of factor resources and the distortions in labor and capital prices, resulting in a decline in innovation efficiency, especially in labor markets ( Qiao *et al*., 2021; Qiao *et al*. ,2022). In addition, innovation input factors do not coexist seamlessly, and a bias toward favoring one type of input factor over another may emerge (Yang *et al*., 2020).

The main marginal contribution of this paper is that we decompose innovation efficiency into three types for comparison: labor innovation efficiency, capital innovation efficiency, and comprehensive innovation efficiency, which differ in the input factors in innovation activities. The importance of categorizing innovation efficiency into three types stems from the complex information it provides about the various contributions of labor and capital to overall innovation outcomes. By examining labor innovation efficiency separately, we may discover specific areas where human capital influences innovation, revealing insights that might otherwise be overlooked when considering innovation efficiency as a single aggregate measure. Similarly, isolating capital innovation efficiency allows us to assess how certain financial investments influence innovation performance. This distinction enables policymakers and business leaders to implement specific strategies for increasing innovation in state-owned and non-state-owned firms, resulting in more effective resource allocation and increased market competitiveness. Furthermore, our methodology is analogous to taking partial derivatives in a production function, reflecting a deeper understanding of economics. We can examine the marginal yields by modifying one input while maintaining the others constant. For example, labor innovation efficiency can be deemed as the marginal innovative yield of labor, and capital innovation efficiency as the marginal innovative yield of capital. This mathematical viewpoint highlights the unique contributions of every kind of input, enabling a more focused assessment of innovation efficiency. Even though we are not yet able to completely isolate outputs that correspond to certain inputs, we believe that further study will make it possible to calculate innovation efficiency more precisely, which will emphasize how important this distinction is.

We use the data of listed companies from 2015 to 2021 to empirically study the true difference between state-owned and non-state-owned enterprises and to conduct robust checks. The results show that regarding innovation, SOEs are less efficient at investing in R&D and human capital than NSOEs, and their investments in human capital result in a more significant loss of efficiency. Further analysis verifies that equity incentives will enhance labor innovation efficiency, while tax incentives will stimulate capital innovation efficiency. However, this effect only remains valid within a specific range of equity incentives.

In conclusion, the innovations in our paper are threefold: (1) we conducted a comparative analysis of innovation efficiency from both labor and financial perspectives, conclusively demonstrating that SOEs experience a decline in innovation efficiency; (2) we delved into two potential channels that could enhance labor and capital innovation efficiency in NSOEs, thereby providing SOEs with actionable insights for emulation and self-improvement; (3) leveraging the most recent data, we assessed whether there has been any improvement in innovation efficiency over recent years.

The rest of this paper is organized as follows. Section 2 provides a theoretical analysis and proposes our hypothesis. Section 3 describes the research data and model, while Section 4 presents the main empirical results and several robustness checks. Section 5 further analyzes the mechanism, and section 6 compares the heterogeneity. Finally, Section 7 summarizes our conclusions.

## 2. Theory and Hypotheses

Existing research frequently considers two crucial paths to innovation activities together—human and capital inputs (Zhong *et al*., 2021), when analyzing the inputs to organizations' innovation activities. An amount of the innovation input elements of companies can be covered by some research that measures the innovation efficiency of firms using both capital and people as input variables, such as capital stock, the number of highly trained workers (Cruz-Cázares *et al*., 2013), R&D people (Piao *et al*., 2022), and R&D expenditures by enterprises (O'Regan *et al*., 2006). According to our research, R&D costs more naturally represent the capital that businesses invest in innovation. Because highly skilled workers are still likely to be involved in the company's production activities, R&D staff can be seen as the human cost that businesses pay in innovation activities. Using the concept of separating labor and capital in the input variables, we presuppose that the input factor of capital innovation efficiency is the R&D expenditures that enterprises spend on innovation activities, while the input factor of labor innovation efficiency is only the human capital enterprises invest for innovation, and finally, the input factors of comprehensive innovation efficiency are both R&D expenses and human capital.

### *2.1. Labor innovation efficiency*

Labor innovation efficiency refers to the amount of innovation produced per unit of R&D staff.

From the manpower innovation perspective, it is imperative to acknowledge that innovation is a product of the collaborative efforts between executives and employees inside an organization and that neither can be accomplished in isolation (Fredrickson *et al*., 2010; Lou *et al*., 2023). Nevertheless, since managers of SOEs are appointed, the current risks borne by innovative activities are far more significant than the potential expected returns in the future. Compared with NSOEs, managers of SOEs generally have "short-sighted behavior", which means that they pay more attention to business activities that can obtain profits in the present, resulting in lagging behind labor innovation efficiency. In addition, the employees of state-owned firms are frequently less motivated to engage in creative activities because they have higher job security, better welfare support from the government, and are not required to compete in the market (Chang *et al*., 2019). In contrast, NSOEs have more energy and motivation, which manifests in a closer relationship between employee creativity and corporate innovation (Liu *et al*., 2017). Besides, we recognize that SOEs need to improve motivating management; they are currently investing far less in innovative employees than NSOEs. In other words, they invest too little in employee recruitment and termination decisions, leaving them with a poor ability to respond to changes in demand shocks (Lane *et al*., 1998). Based on the discussion above, we suppose the first hypothesis:

H1. *The labor innovation efficiency of state-owned enterprises is lower than that of non-state-owned enterprises.*

### *2.2. Capital innovation efficiency*

We now focus on the efficiency of financial innovation, comparing firms with different ownership structures, and assessing the proportion of a firm's innovation expenditure that is a sunk cost and the proportion that results in real innovative outputs. Capital innovation efficiency indicates the amount of innovation produced per unit of R&D expenses. We acknowledge that SOEs have credit guarantees from the government, which enables banks and other lending institutions to be more willing to provide loans (Dong *et al*., 2021), while NSOEs have a high threshold for obtaining financing and generally are faced with credit discrimination. Research and development (R&D) intensity can be increased by SOEs, but high R&D efficiency is not guaranteed (Qian and Xu, 1998). Even if they can keep a tight relationship with the government, SOEs have to deal with the issue of soft budget constraints (Rawski, 1997). The bank typically does not require the enterprise to file for bankruptcy and liquidation when there is a soft budget constraint between the bank and the lending enterprise. Instead, the government and banking institutions will underwrite the enterprise and assist it in getting out of trouble, even if the enterprise fails to perform on time due to R&D failure. Soft budget restrictions can directly affect SOE managers' expectations for innovation projects by making them less risk-averse in the face of failure (Maskin and Xu, 2001). This, in turn, can result in inefficiencies in the public sector's productivity and innovation (Qian and Xu, 1998). However, the capacity to offer larger material returns to innovation in the form of capital gains is a benefit of private ownership over state-owned societies (Zhang *et al*., 2003). In addition, the government also limits the cash holding of SOEs (Walheer and He, 2020), leading to innovation inefficiencies, and compromising investment efficiency by nominating certain members of the management team (S. Chen *et al*., 2011).

Therefore, the strong interaction between companies and the government results in wasted R&D dollars, which in turn leads to inefficiencies in innovation, even if SOEs have access to greater resources and financing channels for innovation. The second hypothesis we propose is that:

H2. *The capital innovation efficiency of non-state-owned enterprises is higher than that of state-owned enterprises.*

*2.3. Comprehensive innovation efficiency*

In reality, R&D funds and human capital investment are essential sources of innovation investment for all enterprises. Comprehensive innovation efficiency is the innovation outcome per unit of input, where inputs include R&D personnel and R&D costs, which are closer to the true innovation efficiency of firms. Therefore, we will take into account the realistic and practical circumstances in this section. The root reason why innovation efficiency in SOEs is lower lies in the state-owned structure. As we have discussed above, in principle, maximizing innovation efficiency requires the consistency of innovation revenue rights and innovation control rights. The state-owned attributes of enterprises have caused a mismatch between income and control, inevitably leading to a loss of innovation efficiency although they can access more innovative resources (Chang *et al*., 2019). Besides, the governance structure of SOEs tends to be relatively intricate, characterized by elongated decision-making chains and intricate approval procedures. This complexity can hinder the progression of innovative endeavors and impede swift market responsiveness. Conversely, NSOEs exhibit greater agility and adaptability in market competition, enabling them to swiftly detect market shifts and promptly adjust their strategies. Furthermore, to thrive and expand within a fiercely competitive market landscape, NSOEs are compelled to continually innovate and refine their offerings to cater to evolving customer demands, while SOEs may encounter a lack of sufficient incentives for innovation, potentially stemming from their monopolistic positions or their reliance on policy support. Therefore, based on the principal-agent problem and the policy constraints faced by SOEs, we assume that NSOEs have greater comprehensive innovation efficiency advantages.

Taking labor and financial elements into account, many national policies have begun to pay attention to the financing constraints of NSOEs, and these problems have gradually been alleviated. At the same time, the political relationships that gave SOEs advantages in the early stage also restricted their development later. Moreover, NSOEs include many high-tech enterprises and industry leaders, and their financing problems will not greatly trouble the innovation efficiency of enterprises. The advantage of SOEs has been narrowing. However, unlike the improved financing situation of NSOEs, the human capital structure and innovation incentive mechanism of SOEs have yet to be substantially optimized. SOEs are overstaffed, and some political constraints brought about by state-owned attributes make innovation trial and error costly. Employees still focus on "stability" as their primary goal and often lack the motivation to innovate. This illustrates that there is still a significant gap in labor innovation efficiency between the two types of ownership enterprises. In addition, we also need to take into account that innovation activities are inherently human capital-intensive, which makes innovation highly dependent on human capital, and innovation efficiency mainly relies on human capital (Holmstrom, 1989). Human capital can either directly affect or indirectly improve innovation efficiency based on factors such as educational background (Kato *et al*., 2015). Therefore, the third hypothesis proposed in this article is:

H3. *The comprehensive innovation efficiency of non-state-owned enterprises is higher than that of state-owned enterprises.*

## 3. Methods and Results

### *3.1. Data*

We set up a panel dataset for the listed companies over the period from 2015 to 2021, mainly collected from China – the China Stock Market and Accounting Research (CSMAR). After selection, this dataset contains 3,721 companies and 20,391 observed samples.

Table 1 shows the intensity of human and financial inputs in the sample firms, tentatively confirming our hypothesis that NSOEs are more innovative. The mean and median proportion of innovative personnel in NSOEs are significantly higher than that in SOEs, and SOEs allocate less funding to research and development. Specifically, the average ratio of R&D investment to operating revenue for NSOEs is considerably greater than that for SOEs.

**Table 1**
Intensity of human and capital inputs.

| | SOE | N | mean | median | sd | min | max |
|---|---|---|---|---|---|---|---|
| Proport of R&D personnel to the total number of employees | 0 | 14387 | 0.171 | 0.135 | 0.143 | 0 | 0.945 |
| | 1 | 6004 | 0.117 | 0.092 | 0.122 | 0 | 0.882 |
| | Total | 20391 | 0.155 | 0.125 | 0.139 | 0 | 0.945 |
| Proport of R&D investment to the operating revenue | 0 | 14387 | 0.078 | 0.041 | 2.647 | 0 | 317.288 |
| | 1 | 6004 | 0.032 | 0.026 | 0.041 | 0 | 0.886 |
| | Total | 20391 | 0.065 | 0.037 | 2.222 | 0 | 317.288 |

### *3.2. Dependent variables*

We use two input indicators when calculating innovation efficiency: the number of corporate innovators and corporate R&D expenditures. The input variable of labor innovation efficiency is corporate innovators, capital innovation efficiency is represented by R&D expenses and comprehensive includes both of them. Meanwhile, only one output indicator was added to the calculation: the total number of invention patents, utility models, and design patents. While some literature uses intangible assets and revenue from new product sales as output variables of innovation, this paper argues that measures of innovation efficiency should not include firms' ability to profit from innovation; rather, they should concentrate on the results of firms' innovations (Cruz-Cázares *et al*., 2013).

As for the measurements of innovation efficiency, we have identified three methods to measure innovation efficiency. The first is the direct ratio method calculated by the output/input (Hirshleifer *et al*., 2013), which is easier to obtain and directly perceived. We use only the values obtained from this type of calculation method for robustness testing (IE_P_P, IE_P_M). While numerical comparisons are highly intuitive, the ratio cannot account for multiple inputs and outputs, nor can it address random errors or technical inefficiencies. So, the second non-parametric method, data envelopment analysis (DEA), which covers many factors and then becomes the most popular measurement to calculate IE (Guan and Chen, 2012), can solve this dilemma. The third parametric method is the stochastic frontier approach (SFA). Compared with DEA, SFA needs to assume that there is a specific function between the input and output but can yield more accurate results that account for the influence of random errors; however, the topics discussed by SFA and DEA are similar. Thus, the method we use to calculate is the data envelopment analysis (DEA) due to its effectiveness and comprehensiveness. Since the ratio calculation is more straightforward with one input and one output, we calculate it as a robust check. All data are processed to be dimensionless before we calculate.

Under specific situations, linear programming is the fundamental feature of DEA measurement of efficiency. The idea is to map decision-making units with various inputs and outputs onto the production frontier surface of DEA, which is also regarded as a Pareto optimum solution set, aiming to minimize input or maximize output. Thus, the subjectivity and complexity of weight selection in the traditional technique are avoided with DEA method, which does not require any weight hypothesis or data dimensional processing during the evaluation. We utilized the output-oriented variable returns to scale DEA-BCC model, and the model settings are outlined below.

$$\min\left[\theta-\varepsilon\left(s^{-}+s^{+}\right)\right]$$
$$s.t.\begin{cases}\sum_{i=1}^{n}\lambda_i x_i+s^{-}=\theta x_0\\ \sum_{i=1}^{n}\lambda_i y_i-s^{+}=y_0\\ \sum_{i=1}^{n}\lambda_i=1\\ \lambda_i,s^{-},s^{+}\geq 0;i=1,2,3,\ldots n\end{cases}\tag{1}$$

Where n is the number of decision-making units, $\lambda_i$ are the decision-making individual weights, and $x_i$, $y_i$ are the inputs and outputs, respectively. The $\theta \in [0,1]$ stands for the innovation efficiency of the firm, and $s_1$, $s_2$ are the values of excess inputs and insufficient outputs, respectively. The variable $\varepsilon$ is a non-Archimedean infinitesimal quantity. When $\theta = 1$, it means that the DEA is in a fully efficient state; otherwise, the DEA is in an inefficient state with an efficiency loss of 1-$\theta$. The average annual innovation efficiency of businesses with various ownership structures is determined in Fig. 1 NSOEs are shown in the left panel, while SOEs are shown in the right panel. Due to the pandemic, the innovation efficiency of SOEs and NSOEs declined significantly in 2021 after showing an increasing trend until 2020, respectively. The comprehensive innovation efficiency is the highest of the three, supporting our belief that human and financial resources are essential for innovation-related activities.

### *3.3. Independent variable*

The explanatory variable is a dummy variable of corporate ownership, meaning that the value of SOEs is 1 and that of NSOEs is 0 specifically.

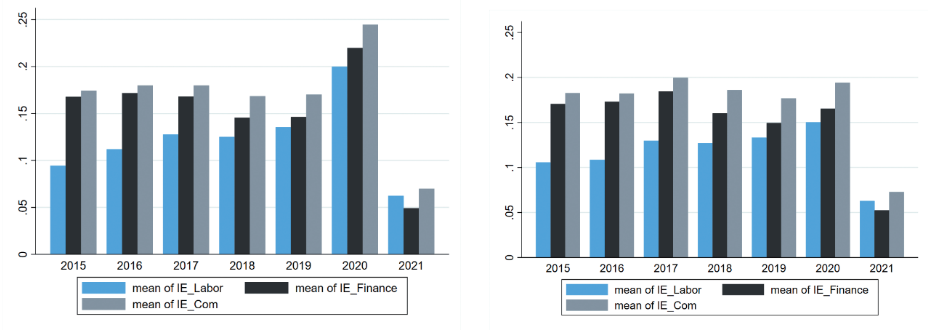


**Fig. 1.** Average annual innovation efficiency of enterprises (SOEs on the right).

*3.4. Control variables*

We select nine control variables in terms of both the financial and operational characteristics of the firm to include the model. We choose regular financial indicators like net profit margin on total assets (ROA), asset-liability ratio (Lev) (Piao *et al.*, 2022), TobinQ, cash flow ratio (Cashflow) and revenue growth rate (Growth) (Fiorentino *et al.*, 2020). Board size (Board), percentage of independent directors (Indep) (Ongsakul *et al.*, 2022), the shareholding ratio of the largest shareholder (TOP1), and whether the company is audited by a Big 4 firm (Big4) (Hao, 2023) are included in the operational characteristics.

*3.5. Mechanism variables*

The first adjustment variable we chose is equity incentives (EI) for managers, which can make a difference in human capital innovation efficiency. The calculation method for this variable is based on existing literature (Chen and Zhang, 2023). The second adjustment variable is tax incentives (TI) because government financial support can effectively alleviate the pressure on enterprises' innovation efficiency in capital investment. The calculation is tax refunds received/(tax refunds received + taxes paid) (Liu, 2016).

*3.6. Grouping variables*

To explore the variations in different industries and competition environments, we divided all samples into two groups using two methods. The first one (HighTech) is that high-technology corporations are defined as 1 and others are 0. The second method is industry type (Type), and the enterprise is labor-intensive = 1, technology-intensive = 2, capital-intensive = 3. The third method (Size) calculates the size of each firm, with 1 indicating above average and 0 indicating below average. Specific variable calculation methods and symbols are shown in Table 2.

**Table 2**
Variable declaration.

| | Variable | Meaning | Calculation |
|---|---|---|---|
| Explained variable | IE_Labor | Labor Innovation Efficiency | DEA (input indicator is the number of innovators) |
| | IE_Finance | Capital innovation efficiency | DEA (input indicator is R&D expenses) |
| | IE_Com | Comprehensive Innovation Efficiency | DEA (input indicators are the number of innovators and R&D expenses) |
| Explanatory variable | SOE | Ownership | SOEs = 1, otherwise= 0 |

**Table 2. (continued)**

| | Variable | Meaning | Calculation |
|---|---|---|---|
| Control variable | ROA | Net profit margin on total assets | Net profit/average balance of total assets |
| | Lev | Asset-liability ratio | Total liabilities at year-end/total assets at year-end |
| | TobinQ | TobinQ value | (Market value of tradable shares + number of non-tradable shares × net assets per share + book value of liabilities) / total assets |
| | Cashflow | Cash flow ratio | Net linear runoff from operating activities/total assets |
| | Growth | Revenue growth rate | Current year's operating income/last year's operating income -1 |
| | Board | Board size | Ln(the number of board members) |
| | Indep | Percentage of independent directors | Number of independent directors/number of directors |
| | TOP1 | The shareholding ratio of the largest shareholder | Number of shares held by the largest shareholder/ total number of shares |
| | Big4 | Audited by Big 4 | Audited by Big 4=1,otherwise=0 |
| Mechanism variable | EI | Equity incentives | (Chen,2022) |
| | TI | Tax incentives | tax refunds received/(tax refunds received + taxes paid) |
| Group variable | HighTech | High technology industry | High technology industry =1 , otherwise=0 |
| | Type | Industry type | Labor-intensive = 1, technology-intensive = 2, capital-intensive = 3 |
| | Size | The size of the corporate | Above the average of size=1, otherwise=0 |

*3.7. Regression model*

After the Hausmann test, the original hypothesis that the random disturbance term is not correlated with the explanatory variables is significantly rejected at the 1% confidence level using labor innovation efficiency, financial innovation efficiency, and comprehensive innovation efficiency as dependent variables, so this paper adopts a fixed effects model. We built a two-way fixed regression model to explore the relationship between innovation efficiency and ownership as shown below.

$$y_{i,t} = \beta_0 + \beta_1 SOE_{i,t} + \beta_2 X_{i,t} + \eta_i + \gamma_t + \varepsilon_{i,t} \tag{2}$$

Where i and t denote firm and year respectively. The $y_{i,t}$ is the innovation efficiency, and $x_{i,t}$ are control variables. To control what varies by year and firm, $\gamma_t$ is set as the year fixed effects and $\eta_i$ is set as the firm fixed effects. And $\varepsilon_{i,t}$ is the error term.

## 4. Results

*4.1. Testing the direct effect*

A descriptive analysis of all the data is presented in Table 3. With a mean value of just 0.121, labor innovation efficiency is the lowest of the innovation efficiencies, while the mean value of 0.168 indicates that integrated innovation efficiency is the highest, in line with Fig. 1. By standard deviation, there is little difference in control variables among firms except for Indep, with a figure of 28.570. A large part of the corporate has little tax incentives, and the average is only 0.160. Over half of the companies in our sample are in the high-tech sector and of a small scale.

**Table 3**
Summary statistics.

| Variable | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| IE_Labor | 20391 | 0.121 | 0.178 | 0.010 | 1.000 |
| IE_Finance | 20391 | 0.149 | 0.185 | 0.010 | 1.000 |
| IE_Com | 20391 | 0.168 | 0.206 | 0.010 | 1.000 |
| SOE | 20391 | 0.294 | 0.456 | 0.000 | 1.000 |
| ROA | 20391 | 0.041 | 0.070 | -0.358 | 0.261 |
| Lev | 20391 | 0.405 | 0.195 | 0.054 | 0.884 |
| TobinQ | 20391 | 2.131 | 1.388 | 0.813 | 11.698 |
| Cashflow | 20391 | 0.050 | 0.065 | -0.167 | 0.259 |
| Growth | 20391 | 0.184 | 0.386 | -0.572 | 3.324 |
| Board | 20391 | 2.106 | 0.196 | 1.609 | 2.708 |
| Indep | 20391 | 37.792 | 5.381 | 28.570 | 60.000 |
| TOP1 | 20391 | 33.519 | 14.202 | 8.899 | 73.820 |
| Big4 | 20391 | 0.054 | 0.226 | 0.000 | 1.000 |
| IE_P_P | 20391 | 1.218 | 1.793 | 0.100 | 10.000 |
| IE_P_M | 20391 | 1.499 | 1.884 | 0.100 | 10.001 |
| EI | 20391 | 0.307 | 0.352 | 0.000 | 0.983 |
| TI | 20391 | 0.160 | 0.204 | 0.000 | 0.825 |
| HighTech | 20391 | 0.654 | 0.476 | 0.000 | 1.000 |
| Type | 20391 | 2.038 | 0.688 | 1.000 | 3.000 |
| Size | 20391 | 0.441 | 0.497 | 0.000 | 1.000 |

*Notes: All results retain three decimals.*

### *4.2. Baseline regression*

As we can see in Table 4, the explained variable in columns (1) and (2) is labor innovation efficiency, while capital innovation efficiency is shown in columns (3) and (4), and comprehensive innovation efficiency is presented in columns (5) and (6). Among them, columns (2), (4) and (6) include the control variables in the regression model. When considering human capital as the only input indicator, the coefficient is significantly negative. However, the significance decreases when we consider capital innovation efficiency. This indicates that NSOEs are gaining effective innovation through human capital and financial investment, despite the very weak advantage of capital innovation efficiency. More interestingly, we examined comprehensive innovation efficiency in columns (5) and (6) and found that NSOEs are more efficient with these two input elements in those columns.

Table 4
Baseline regression.

| Variable | (1) IE_Labor | (2) IE_Labor | (3) IE_Finance | (4) IE_Finance | (5) IE_Com | (6) IE_Com |
|---|---|---|---|---|---|---|
| SOE | -0.016*** | -0.015*** | -0.008*** | -0.006* | -0.008** | -0.007** |
| | (-6.513) | (-5.385) | (-2.921) | (-1.945) | (-2.519) | (-2.081) |
| ROA | | 0.088*** | | 0.031 | | 0.051** |
| | | (4.622) | | (1.559) | | (2.289) |
| Lev | | -0.086*** | | -0.106*** | | -0.112*** |
| | | (-10.736) | | (-12.805) | | (-12.330) |
| TobinQ | | -0.010*** | | -0.009*** | | -0.011*** |
| | | (-12.813) | | (-10.325) | | (-11.396) |
| Cashflow | | -0.038* | | -0.052** | | -0.068*** |
| | | (-1.780) | | (-2.363) | | (-2.795) |
| Growth | | 0.015*** | | 0.008** | | 0.004 |
| | | (4.339) | | (2.122) | | (0.954) |
| Board | | 0.006 | | 0.014* | | 0.010 |
| | | (0.805) | | (1.755) | | (1.085) |
| Indep | | 0.000 | | -0.000 | | 0.000 |
| | | (1.549) | | (-0.096) | | (0.698) |
| TOP1 | | 0.001*** | | 0.001*** | | 0.001*** |
| | | (7.444) | | (6.854) | | (8.553) |
| Big4 | | 0.021*** | | 0.013** | | 0.023*** |
| | | (3.299) | | (2.224) | | (3.254) |
| _cons | 0.126*** | 0.124*** | 0.151*** | 0.161*** | 0.170*** | 0.179*** |
| | (82.182) | (5.240) | (96.110) | (6.606) | (96.780) | (6.429) |
| N | 20391 | 20391 | 20391 | 20391 | 20391 | 20391 |
| Adj $R^2$ | 0.053 | 0.071 | 0.076 | 0.091 | 0.061 | 0.078 |
| YearFE | YES | YES | YES | YES | YES | YES |
| IndustryFE | YES | YES | YES | YES | YES | YES |

*Notes: The numbers in parentheses are t-values, and the standard deviation is based on robust standard error. The result retains three decimals. *denotes significance at the 10%, **5%, and ***1% level.*

*4.3. Robustness*

*4.3.1. Alternative measurements*

As the paper shows above, the output is the total number of patents, and the inputs are human capital measured by the total number of innovators and investment measured by the R&D investment, respectively. We use the direct ratio method calculated by output/input to represent the innovation efficiency. The results of the robust regression are shown in Table 5. In columns (1) and column (2), the dependent variable is labor innovation efficiency, while columns (3) and column (4) are capital innovation efficiency, and the comprehensive innovation efficiency cannot be simply calculated by a ratio. The regression results are similar to the baseline, indicating that SOEs incur losses both in finance and labor, especially more pronounced in terms of labor.

**Table 5**
Robust regression: alternative measurements.

| Variable | (1) IE_P_P | (2) IE_P_P | (3) IE_P_M | (4) IE_P_M |
|---|---|---|---|---|
| SOE | -0.165*** | -0.148*** | -0.077*** | -0.055* |
| | (-6.469) | (-5.372) | (-2.765) | (-1.827) |
| ROA | | 0.883*** | | 0.298 |
| | | (4.624) | | (1.443) |
| Lev | | -0.868*** | | -1.063*** |
| | | (-10.680) | | (-12.686) |
| TobinQ | | -0.102*** | | -0.094*** |
| | | (-12.615) | | (-10.234) |
| Cashflow | | -0.389* | | -0.526** |
| | | (-1.787) | | (-2.366) |
| Growth | | 0.152*** | | 0.073** |
| | | (4.308) | | (1.983) |
| Board | | 0.070 | | 0.140* |
| | | (0.874) | | (1.696) |
| Indep | | 0.004 | | -0.001 |
| | | (1.552) | | (-0.197) |
| TOP1 | | 0.007*** | | 0.007*** |
| | | (7.429) | | (6.769) |
| Big4 | | 0.215*** | | 0.140** |
| | | (3.289) | | (2.265) |
| _cons | 1.266*** | 1.232*** | 1.521*** | 1.643*** |
| | (81.765) | (5.149) | (95.026) | (6.661) |
| N | 20391 | 20391 | 20391 | 20391 |
| Adj $R^2$ | 0.052 | 0.069 | 0.070 | 0.085 |
| YearFE | YES | YES | YES | YES |
| IndustryFE | YES | YES | YES | YES |

*Notes: The numbers in parentheses are t-values, and the standard deviation is based on robust standard error. The result retains three decimals. *denotes significance at the 10%, **5%, and ***1% level.*

*4.3.2. Re-screening samples and data*

A small proportion of firms in the sample used in the baseline regression incurred losses in the years of operation. We believe that these firms are in the start-up phase and invest a lot of financial and human resources in innovation activities even though they are not doing well in their main business. However, in this part of the robustness test, we have to recognize that the poorly run firms may not be able to invest too much in innovative activities, so they are excluded from the sample and regressed again. The results in Table 6 are similar to those of the baseline regression.

**Table 6**
Robust regression: re-screening samples and data.

| Variable | (1) IE_Labor | (2) IE_Finance | (3) IE_Com |
|---|---|---|---|
| SOE | -0.014*** | -0.007** | -0.008** |
| | (-4.809) | (-2.294) | (-2.358) |
| ROA | 0.209*** | 0.044 | 0.075* |
| | (5.387) | (1.093) | (1.725) |
| Lev | -0.090*** | -0.111*** | -0.117*** |
| | (-10.116) | (-12.032) | (-11.645) |
| TobinQ | -0.013*** | -0.011*** | -0.014*** |
| | (-14.360) | (-11.053) | (-12.209) |
| Cashflow | -0.037 | -0.037 | -0.046* |
| | (-1.516) | (-1.481) | (-1.670) |
| Growth | 0.013*** | 0.007* | 0.003 |
| | (3.650) | (1.762) | (0.749) |
| Board | 0.005 | 0.013 | 0.007 |
| | (0.591) | (1.495) | (0.753) |
| Indep | 0.000 | -0.000 | 0.000 |
| | (1.507) | (-0.222) | (0.517) |
| TOP1 | 0.001*** | 0.001*** | 0.001*** |
| | (6.957) | (6.538) | (8.161) |
| Big4 | 0.021*** | 0.013** | 0.023*** |
| | (3.143) | (2.047) | (3.170) |
| _cons | 0.127*** | 0.171*** | 0.190*** |
| | (5.028) | (6.672) | (6.532) |
| N | 18106 | 18106 | 18106 |
| Adj $R^2$ | 0.074 | 0.093 | 0.080 |
| YearFE | YES | YES | YES |
| IndustryFE | YES | YES | YES |

*Notes: The numbers in parentheses are t-values, and the standard deviation is based on robust standard error. The result retains three decimals. *denotes significance at the 10%, **5%, and ***1% level.*

*4.3.3. Inclusion of shares impact*

We must pay attention to the mixed-ownership reform in Chinese companies, which allows state-owned shares to exist in NSOEs and non-state-owned shares in SOEs. The baseline regression may be disturbed by the proportion of shares that differ from own property rights. We added a new control variable calculated as the cumulative shareholding ratio of state-owned shareholders among the top ten shareholders. The results in Table 4 show that innovation efficiency is rarely impacted. Therefore, we can conclude that the difference in innovation efficiency between SOEs and NSOEs contributes to property rights rather than the ownership of the shares.

**Table 7**
Robust regression: inclusion of shares impact.

| Variable | (1) IE_Labor | (2) IE_Finance | (3) IE_Com |
|---|---|---|---|
| SOE | -0.019*** | -0.008*** | -0.010*** |
| | (-6.660) | (-2.697) | (-2.816) |
| ROA | 0.088*** | 0.031 | 0.051** |
| | z | (1.565) | (2.295) |
| Lev | -0.086*** | -0.105*** | -0.112*** |
| | (-10.720) | (-12.792) | (-12.319) |
| TobinQ | -0.010*** | -0.009*** | -0.011*** |
| | (-12.541) | (-10.149) | (-11.219) |
| Cashflow | -0.038* | -0.052** | -0.068*** |
| | (-1.781) | (-2.363) | (-2.796) |
| Growth | 0.014*** | 0.007** | 0.003 |
| | (4.098) | (1.974) | (0.804) |
| Board | 0.006 | 0.014* | 0.010 |
| | (0.731) | (1.708) | (1.039) |
| Indep | 0.000 | -0.000 | 0.000 |
| | (1.574) | (-0.080) | (0.713) |
| TOP1 | 0.001*** | 0.001*** | 0.001*** |
| | (6.827) | (6.414) | (8.089) |
| Big4 | 0.022*** | 0.014** | 0.023*** |
| | (3.351) | (2.260) | (3.288) |
| Proportion_StateOwn | 0.034*** | 0.023** | 0.025** |
| | (3.219) | (2.080) | (2.017) |
| _cons | 0.126*** | 0.162*** | 0.180*** |
| | (5.312) | (6.656) | (6.473) |
| N | 20391 | 20391 | 20391 |
| Adj $R^2$ | 0.071 | 0.091 | 0.078 |
| YearFE | YES | YES | YES |
| IndustryFE | YES | YES | YES |

*Notes: The numbers in parentheses are t-values, and the standard deviation is based on robust standard error. The result retains three decimals. *denotes significance at the 10%, **5%, and ***1% level.*

*4.3.4. Endogenous treatment*

To address the potential endogeneity of the model—that is, the possibility that variations in innovation efficiency are caused by unidentified factors, we match sets of NSOEs with comparable attributes to SOEs using the PSM technique. Although a company's ownership structure is predetermined at the time of its founding by its investors and operational procedures, the ownership determination may also be influenced by industry access policies, development histories, and various city geographic locations. In China, in particular, the number of NSOEs is larger in the coastal areas where reform and opening-up occurred earlier, whereas businesses operating in sectors such as telecommunications and petroleum are primarily SOEs. Therefore, for the closest neighbor PSM matching, groups like SOEs are identified using city and industry. The kernel density map before and after matching is depicted in Fig. 2, where we can clearly see that the difference between the treated (SOEs) and control groups is smaller. The results of the balancing test in Table 8 show that the variables' standardized variation is under 10% and the t value after matching is less than 1, which indicates that PSM could avoid, to some extent, the impact of systematic differences in observable variables.

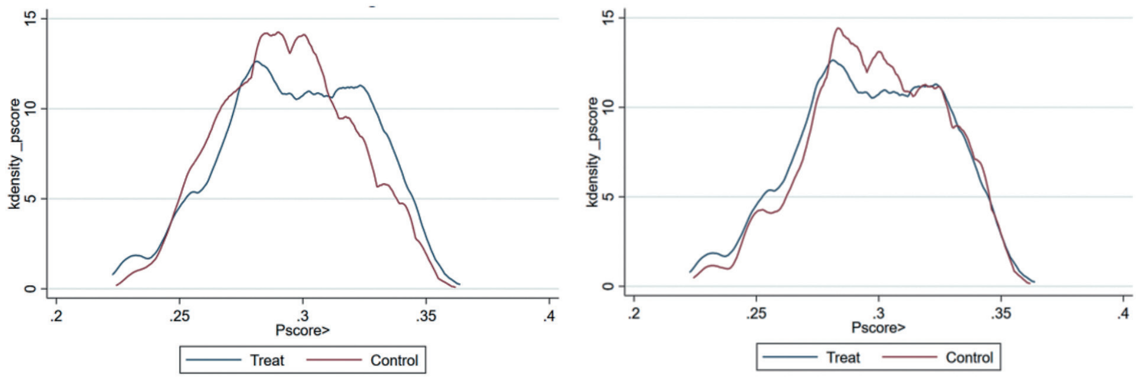


**Fig. 2.** Kernel density map (after matching on the right).

**Table 8**
Endogenous treatment: PSM matching results.

| Variable | Group | Mean | | Bias | T-test | |
|---|---|---|---|---|---|---|
| | | Treat | Control | | t | P>\|t\| |
| City | Unmatched | 143.56 | 153.89 | -10.2 | -6.71 | 0.000 |
| | Matched | 143.55 | 142.62 | 0.9 | 0.50 | 0.620 |
| Industry | Unmatched | 24.634 | 23.727 | 8.6 | 5.76 | 0.000 |
| | Matched | 24.625 | 24.51 | 1.1 | 0.58 | 0.565 |

Then we re-estimate the regression using the two groups as dependent variables after PSM matching and the results in Table 9 indicate that the innovation efficiency in NSOEs are significantly higher than that in SOEs.

**Table 9**
Endogenous treatment: baseline regression after PSM matching.

| Variable | (1) IE_Labor | (2) IE_Finance | (3) IE_Com |
|---|---|---|---|
| Treat | -0.015*** | -0.006* | -0.007** |
| | (-5.385) | (-1.945) | (-2.081) |
| ROA | 0.088*** | 0.031 | 0.051** |
| | (4.622) | (1.559) | (2.289) |
| Lev | -0.086*** | -0.106*** | -0.112*** |

| | | | |
|---|---|---|---|
| | (-10.736) | (-12.805) | (-12.330) |
| TobinQ | -0.010*** | -0.009*** | -0.011*** |
| | (-12.813) | (-10.325) | (-11.396) |
| Cashflow | -0.038* | -0.052** | -0.068*** |
| | (-1.780) | (-2.363) | (-2.795) |
| Growth | 0.015*** | 0.008** | 0.004 |
| | (4.339) | (2.122) | (0.954) |
| Board | 0.006 | 0.014* | 0.010 |
| | (0.805) | (1.755) | (1.085) |
| Indep | 0.000 | -0.000 | 0.000 |
| | (1.549) | (-0.096) | (0.698) |
| TOP1 | 0.001*** | 0.001*** | 0.001*** |
| | (7.444) | (6.854) | (8.553) |
| Big4 | 0.021*** | 0.013** | 0.023*** |
| | (3.299) | (2.224) | (3.254) |
| _cons | 0.124*** | 0.161*** | 0.179*** |
| | (5.240) | (6.606) | (6.429) |
| N | 20391 | 20391 | 20391 |
| Adj $R^2$ | 0.071 | 0.091 | 0.078 |
| YearFE | YES | YES | YES |
| IndustryFE | YES | YES | YES |

*Notes: The numbers in parentheses are t-values, and the standard deviation is based on robust standard error. The result retains three decimals. *denotes significance at the 10%, **5%, and ***1% level.*

## 5. Mechanism

The following analysis will discuss two channels divided according to the categories of inputs to innovation efficiency.

*5.1. Mechanism of labor innovation efficiency: equity incentive*

Talking about the channel to improve innovation efficiency related to labor, we should consider what companies do to encourage researchers to get to work and gain more achievements. The secret to promoting innovation efficiency lies in solving the fundamental problem of the mismatch between the profit right and the control right and improving the income that managers can get in the innovation activities. In fact, one of the effective solutions is for managers to own shares and even become owners themselves. For most NSOEs, management shareholding is one of the mechanisms to promote managers' innovative efforts. Firstly, giving managers equity will enable them to attach greater importance to the enterprise's research and development because they have the same goals as other shareholders to achieve the maximum return. Meanwhile, equity incentives decrease the possibility of short-sighted behavior and agency costs, making innovation active (Lou *et al*., 2023), especially for NSOEs.

Based on equ(1), we added the interaction between ownership and equity incentives into the model as equ(2). But in the regression, we also test the marginal effect on 25%, 50%, and 75% quantiles to make the results more accurate.

$$IE\_Labor_{i,t} = \beta_0 + \beta_1 SOE_{i,t} + \beta_2 EI_{i,t} + \beta_3 SOE_{i,t} * EI_{i,t} + \beta_4 X_{i,t} + \eta_i + \gamma_t + \varepsilon_{i,t} \tag{3}$$

Although the interaction is insignificant, the quantiles show the equity incentive is a channel that negatively affects the innovation efficiency of NSOEs. The regulatory effects depend on the intensity of equity incentives, verified in Table 10, which means equity incentives will only promote the innovation efficiency of NSOEs related to labor when they are over a certain value.

**Table 10**
Mechanism of labor innovation efficiency: equity incentive.

| **Variable** | **IE_Labor** |
|---|---|
| SOE | -0.004 |
| | (-1.342) |
| EI | 0.033*** |
| | (7.533) |
| SOE*EI | -0.018 |
| | (-1.251) |
| Marginal effect | |
| 25% quantile | -0.004 |
| | (-1.343) |
| 50% quantile | -0.006** |
| | (-2.050) |
| 75% quantile | -0.016* |
| | (-1.853) |
| Cons | 0.106*** |
| | (4.452) |
| Controls | YES |
| N | 20391 |
| Adj $R^2$ | 0.0734 |
| YearFE | YES |
| IndustryFE | YES |

*Notes: The numbers in parentheses are t-values, and the standard deviation is based on firm-clustered standard errors. The result retains three decimals. *denotes significance at the 10%, **5%, and * **1% level.*

*5.2. Mechanism of labor innovation efficiency: tax incentives*

The above results show that NSOEs also take more advantage of investing in innovation to improve efficiency than SOEs and now we will explore how NSOEs achieve this.

One of the most powerful instruments for fostering innovation is the tax incentive, which can dramatically raise businesses' financial commitment to R&D (Castellacci and Lie, 2015). It lessens the asymmetry of information and the likelihood of being influenced by other factors, like policy, by allowing firms to design from the bottom up (Chen and Yang, 2019). Therefore, tax incentives provide NSOEs with the chance to increase their R&D efforts, even if they encounter financing challenges. Furthermore, if SOEs do not prioritize innovation activities, incentives may distort overall investment in innovation because SOEs typically have better access to credit or benefit from greater tax breaks (Li *et al.*, 2017).

Based on this, we construct equ (3) like equ (2) to explore the effects of tax incentives on capital innovation efficiency. The results are shown in Table 11. The marginal effect suggests that tax incentives do contribute to the efficiency of NSEs in financial innovation, consistent with theory.

$$IE\_Finance_{i,t} = \beta_0 + \beta_1 SOE_{i,t} + \beta_2 \mathrm{TI}_{i,t} + \beta_3 SOE * \mathrm{TI}_{i,t} + \beta_4 X_{i,t} + \eta_i + \gamma_t + \varepsilon_{i,t} \tag{4}$$

**Table 11**
Mechanism of capital innovation efficiency: tax incentive.

| **Variable** | **IE_Finance** |
|---|---|
| SOE | -0.002 |
| | (-0.505) |
| TI | 0.011 |
| | (1.387) |
| SOE*TI | -0.026** |
| | (-1.965) |
| ROA | 0.032 |
| | (1.590) |
| Lev | -0.105*** |
| | (-12.763) |
| TobinQ | -0.009*** |
| | (-10.293) |
| Cashflow | -0.053** |
| | (-2.409) |
| Growth | 0.008** |
| | (2.099) |
| Board | 0.014* |
| | (1.737) |
| Indep | -0.000 |
| | (-0.139) |
| TOP1 | 0.001*** |
| | (6.785) |
| Big4 | 0.013** |
| | (2.177) |
| _cons | 0.160*** |
| | (6.549) |
| N | 20391.000 |
| Adj $R^2$ | 0.0912 |
| YearFE | YES |
| IndustryFE | YES |

*Notes: The numbers in parentheses are t-values, and the standard deviation is based on firm-clustered standard errors. The result retains three decimals. *denotes significance at the 10%, **5%, and * **1% level.*

## 6. Heterogeneity

*6.1. Heterogeneity in the high-technology industry*

The key to development for companies in the high-technology industry is innovation. We divided samples into two groups (HighTech and LowTech) according to whether they belong to the high technology industry to explore the difference. The heterogeneity results are presented in Table 12.

In our samples, about 70% of high-technology companies are NSOEs, while only 30% are SOEs. The regression results show that among the high-technology enterprises, NSOEs outperform SOEs in labor innovation efficiency, capital innovation efficiency, and comprehensive innovation efficiency. The differences in labor and overall efficiency are more pronounced. NSOEs are the leading force in the high-tech field. In terms of talent utilization, it is clear that the high-tech industry is more capable of attracting the influx of talent, which gives it a greater advantage in labor innovation efficiency. However, regardless of ownership, high-tech enterprises—whether SOEs or NSOEs—benefit from many state preferential policies, leading to a relatively smaller difference in capital innovation efficiency.

**Table 12**
Heterogeneity: high-technology industry.

| Variable | (1) IE_Labor LowTech | (2) IE_Labor HighTech | (3) IE_Finance LowTech | (4) IE_Finance HighTech | (5) IE_Com LowTech | (6) IE_Com HighTech |
|---|---|---|---|---|---|---|
| SOE | 0.001 | -0.023*** | 0.002 | -0.009** | 0.003 | -0.012*** |
| | (0.097) | (-7.322) | (0.476) | (-2.551) | (0.592) | (-2.897) |
| ROA | 0.027 | 0.114*** | -0.006 | 0.049** | -0.007 | 0.079*** |
| | (0.755) | (5.123) | (-0.177) | (2.039) | (-0.176) | (3.018) |
| Lev | -0.044*** | -0.106*** | -0.063*** | -0.126*** | -0.064*** | -0.135*** |
| | (-2.964) | (-11.203) | (-4.476) | (-12.430) | (-3.960) | (-12.376) |
| TobinQ | -0.008*** | -0.011*** | -0.009*** | -0.010*** | -0.011*** | -0.011*** |
| | (-5.126) | (-11.934) | (-5.001) | (-9.096) | (-5.795) | (-9.969) |
| Cashflow | 0.008 | -0.070*** | -0.002 | -0.084*** | 0.005 | -0.114*** |
| | (0.225) | (-2.661) | (-0.042) | (-3.067) | (0.121) | (-3.781) |
| Growth | 0.014** | 0.016*** | 0.007 | 0.008* | 0.008 | 0.001 |
| | (2.164) | (3.873) | (1.088) | (1.741) | (1.106) | (0.168) |
| Board | 0.014 | 0.001 | 0.023 | 0.009 | 0.024 | 0.001 |
| | (0.869) | (0.168) | (1.584) | (0.966) | (1.393) | (0.119) |
| Indep | 0.001** | -0.000 | 0.000 | -0.000 | 0.001* | -0.000 |
| | (2.209) | (-0.121) | (0.474) | (-0.537) | (1.843) | (-0.757) |
| TOP1 | 0.001*** | 0.001*** | 0.000*** | 0.001*** | 0.001*** | 0.001*** |
| | (4.050) | (6.072) | (2.679) | (6.402) | (4.097) | (7.399) |
| Big4 | 0.033*** | 0.007 | 0.015* | 0.009 | 0.039*** | 0.004 |
| | (3.132) | (0.873) | (1.664) | (1.127) | (3.479) | (0.441) |
| _cons | 0.067 | 0.157*** | 0.118*** | 0.183*** | 0.102** | 0.223*** |

**Table 12. (continued)**

| Variable | (1) IE_Labor LowTech | (2) IE_Labor HighTech | (3) IE_Finance LowTech | (4) IE_Finance HighTech | (5) IE_Com LowTech | (6) IE_Com HighTech |
|---|---|---|---|---|---|---|
| | (1.476) | (5.937) | (2.763) | (6.215) | (1.996) | (6.897) |
| N | 7,057 | 13,334 | 7,057 | 13,334 | 7,057 | 13,334 |
| Adj $R^2$ | 0.0497 | 0.0865 | 0.0678 | 0.1054 | 0.0546 | 0.0940 |
| YearFE | YES | YES | YES | YES | YES | YES |
| IndustryFE | YES | YES | YES | YES | YES | YES |

*Notes: The numbers in parentheses are t-values, and the standard deviation is based on firm-clustered standard errors. The result retains three decimals. *denotes significance at the 10%, **5%, and * **1% level.*

*6.2. Heterogeneity of firm size*

We compare the differences by dividing the sample into two groups, large-scale and small-scale, based on the mean value of the firms. The results are presented in Table 13. About 66 percent of NSOEs in the sample were small, while only about 31% of SOEs fell into this category.

The findings demonstrate that SOEs and NSOEs in small businesses differ significantly in terms of efficiency in small businesses, particularly in labor innovation efficiency. In contrast, large companies do not experience this ownership-related difference. We argue that due to their extensive resources and the economies of scale they achieve, large companies can mitigate potential inefficiencies without compromising their performance (Cruz-Cázares *et al*., 2013).

**Table 13**
Heterogeneity: firm size.

| Variable | (1) IE_Labor Small scale | (2) IE_Labor Large scale | (3) IE_Finance Small scale | (4) IE_Finance Large scale | (5) IE_Com Small scale | (6) IE_Com Large scale |
|---|---|---|---|---|---|---|
| SOE | -0.023*** | -0.002 | -0.009* | 0.003 | -0.013** | 0.005 |
| | (-5.113) | (-0.500) | (-1.775) | (0.823) | (-2.317) | (1.090) |
| ROA | 0.140*** | 0.074** | 0.072*** | 0.023 | 0.113*** | 0.038 |
| | (5.571) | (2.403) | (2.748) | (0.711) | (3.895) | (1.071) |
| Lev | -0.102*** | 0.020* | -0.123*** | -0.005 | -0.129*** | 0.010 |
| | (-8.713) | (1.751) | (-10.256) | (-0.431) | (-9.663) | (0.753) |
| TobinQ | -0.012*** | -0.008*** | -0.012*** | -0.005*** | -0.014*** | -0.008*** |
| | (-11.201) | (-6.176) | (-10.231) | (-3.330) | (-10.738) | (-5.054) |
| Cashflow | -0.090*** | 0.078** | -0.108*** | 0.061* | -0.142*** | 0.082** |
| | (-3.009) | (2.545) | (-3.577) | (1.958) | (-4.221) | (2.315) |
| Growth | 0.018*** | 0.013*** | 0.012** | 0.002 | 0.005 | 0.002 |
| | (3.474) | (2.643) | (2.239) | (0.500) | (0.956) | (0.350) |
| Board | 0.005 | 0.019** | 0.009 | 0.029*** | 0.001 | 0.032*** |
| | (0.402) | (1.984) | (0.708) | (2.718) | (0.062) | (2.770) |
| Indep | -0.000 | 0.001** | -0.001 | 0.000 | -0.001 | 0.001* |

**Table 13. (continued)**

| Variable | (1) IE_Labor Small scale | (2) IE_Labor Large scale | (3) IE_Finance Small scale | (4) IE_Finance Large scale | (5) IE_Com Small scale | (6) IE_Com Large scale |
|---|---|---|---|---|---|---|
| | (-0.274) | (2.026) | (-1.271) | (0.726) | (-1.315) | (1.949) |
| TOP1 | 0.001*** | 0.000*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | (5.151) | (3.724) | (3.675) | (4.574) | (5.085) | (5.416) |
| Big4 | 0.060*** | 0.015** | 0.052*** | 0.011* | 0.067*** | 0.018** |
| | (2.695) | (2.380) | (2.634) | (1.764) | (2.966) | (2.565) |
| _cons | 0.162*** | 0.020 | 0.217*** | 0.044 | 0.256*** | 0.023 |
| | (4.038) | (0.703) | (5.586) | (1.403) | (5.691) | (0.655) |
| N | 11,391 | 9,000 | 11,391 | 9,000 | 11,391 | 9,000 |
| Adj $R^2$ | 0.0867 | 0.0839 | 0.1031 | 0.1020 | 0.0903 | 0.0953 |
| YearFE | YES | YES | YES | YES | YES | YES |
| IndustryFE | YES | YES | YES | YES | YES | YES |

*Notes: The numbers in parentheses are t-values, and the standard deviation is based on firm-clustered standard errors. The result retains three decimals. *denotes significance at the 10%, **5%, and * **1% level.*

### *6.3. Heterogeneity of industry type*

Industries are classified based on their main input factor types as labor-intensive, technology-intensive, or capital-intensive. The results of the regression are presented in Table 14. The difference in innovation efficiency between SOEs and NSOEs is not apparent in labor-intensive industries. This suggests that labor-intensive industries require relatively less capital and fewer high-quality labor resources. While high value-added production activities are found in capital- and technology-intensive industries, in technology-intensive industries, when R&D technicians are the primary input, NSOEs exhibit significantly higher labor innovation efficiency compared to SOEs. In capital-intensive industries, capital innovation efficiency is more significant.

**Table 14**
Heterogeneity: industry type.

| Variable | (1) IE_Labor Labor-intensive | (2) IE_Labor Technology-intensive | (3) IE_Labor Capital-intensive | (4) IE_Finance Labor-intensive | (5) IE_Finance Technology-intensive | (6) IE_Finance Capital-intensive | (7) IE_Com Labor-intensive | (8) IE_Com Technology-intensive | (9) IE_Com Capital-intensive |
|---|---|---|---|---|---|---|---|---|---|
| SOE | 0.007 | -0.020*** | -0.023*** | 0.010 | -0.007* | -0.014** | 0.012 | -0.009* | -0.018*** |
| | (1.176) | (-5.600) | (-4.158) | (1.505) | (-1.792) | (-2.537) | (1.610) | (-1.935) | (-2.743) |
| ROA | -0.047 | 0.124*** | 0.085** | -0.086* | 0.071*** | 0.004 | -0.089 | 0.100*** | 0.018 |
| | (-0.948) | (5.079) | (2.141) | (-1.657) | (2.772) | (0.104) | (-1.489) | (3.561) | (0.387) |
| Lev | -0.021 | -0.113*** | -0.087*** | -0.035* | -0.139*** | -0.097*** | -0.036* | -0.148*** | -0.107*** |
| | (-1.098) | (-10.571) | (-5.483) | (-1.905) | (-12.346) | (-5.975) | (-1.734) | (-12.070) | (-6.002) |
| TobinQ | -0.008*** | -0.011*** | -0.009*** | -0.008*** | -0.010*** | -0.009*** | -0.010*** | -0.011*** | -0.012*** |
| | (-3.750) | (-11.129) | (-5.126) | (-3.510) | (-8.380) | (-5.157) | (-4.065) | (-9.112) | (-5.787) |

**Table 14. (continued)**

| Variable | (1) IE_Labor Labor-intensive | (2) IE_Labor Technology-intensive | (3) IE_Labor Capital-intensive | (4) IE_Finance Labor-intensive | (5) IE_Finance Technology-intensive | (6) IE_Finance Capital-intensive | (7) IE_Com Labor-intensive | (8) IE_Com Technology-intensive | (9) IE_Com Capital-intensive |
|---|---|---|---|---|---|---|---|---|---|
| Cashflow | 0.087* | -0.076** | -0.084** | 0.065 | -0.095*** | -0.081* | 0.091* | -0.128*** | -0.099** |
| | (1.886) | (-2.535) | (-1.977) | (1.415) | (-3.111) | (-1.881) | (1.687) | (-3.791) | (-2.075) |
| Growth | 0.013 | 0.013*** | 0.020*** | 0.008 | 0.006 | 0.011 | 0.009 | -0.002 | 0.009 |
| | (1.606) | (3.067) | (2.655) | (0.996) | (1.191) | (1.438) | (1.037) | (-0.367) | (1.041) |
| Board | -0.000 | 0.008 | 0.009 | 0.032* | 0.014 | -0.004 | 0.018 | 0.008 | 0.004 |
| | (-0.004) | (0.798) | (0.517) | (1.780) | (1.304) | (-0.247) | (0.861) | (0.701) | (0.190) |
| Indep | 0.000 | 0.000 | 0.001 | 0.000 | -0.000 | -0.000 | 0.001 | -0.000 | 0.000 |
| | (0.441) | (0.466) | (1.546) | (0.497) | (-0.597) | (-0.277) | (0.839) | (-0.356) | (0.527) |
| TOP1 | 0.001*** | 0.001*** | 0.001*** | 0.000* | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | (2.685) | (5.763) | (3.846) | (1.922) | (5.755) | (3.250) | (2.812) | (6.741) | (4.359) |
| Big4 | 0.031** | 0.007 | 0.029** | 0.009 | 0.014 | 0.011 | 0.035*** | 0.008 | 0.023* |
| | (2.386) | (0.746) | (2.227) | (0.851) | (1.571) | (0.953) | (2.601) | (0.844) | (1.662) |
| _cons | 0.115** | 0.137*** | 0.105** | 0.083 | 0.176*** | 0.211*** | 0.118* | 0.204*** | 0.194*** |
| | (2.197) | (4.500) | (2.058) | (1.588) | (5.368) | (4.230) | (1.926) | (5.650) | (3.320) |
| N | 4,457 | 10,710 | 5,224 | 4,457 | 10,710 | 5,224 | 4,457 | 10,710 | 5,224 |
| Adj $R^2$ | 0.0474 | 0.0901 | 0.0655 | 0.0595 | 0.1102 | 0.0915 | 0.0505 | 0.0976 | 0.0721 |
| YearFE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| IndustryFE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

*Notes: The numbers in parentheses are t-values, and the standard deviation is based on firm-clustered standard errors. The result retains three decimals. *denotes significance at the 10%, **5%, and * **1% level.*

## 7. Conclusion and Discussion

Using public data on Chinese listed companies from 2015 to 2021, we measure and compare the innovation efficiency of SOEs and NSOEs. For the first time, we propose to divide innovation efficiency into labor innovation efficiency, capital innovation efficiency, and comprehensive innovation efficiency. Both the existing experience and empirical results show that the innovation efficiency in NSOEs is higher in terms of labor innovation efficiency. Although SOEs have a wide range of financing sources and low thresholds, the biggest problem is that the right of innovation earnings and the right of control caused by property rights cannot match, resulting in a waste of efficiency. NSOEs avoid this disadvantage and thus have a healthier investment in innovation activities. Therefore, SOEs incur efficiency losses in both human and capital, two important channels of innovation.

Moreover, NSOEs in high-tech industries and of small scale have better performance in innovation efficiency. The industry type will also affect the innovation efficiency of enterprises. NSOEs in technology-intensive industries are better able to promote labor innovation efficiency, while NSOEs in capital-intensive industries have an advantage in promoting capital innovation efficiency.

Based on these analyses, we believe that enterprise innovation efficiency cannot be generalized, and more researches are expected to analyze separately for different sources of innovation input. Enterprises with different ownership systems should learn to give full play to their advantages and avoid their shortcomings. NSOEs should reduce their information asymmetry as much as possible and seek more stable sources of capital. Several strategies can be recommended for state-owned enterprises (SOEs) to enhance their innovation efficiency:

(1) Simplify the approval and decision-making procedures inside SOEs in order to hasten the adoption of creative solutions. This can shorten the time it takes for new goods and services to reach the market, increasing SOEs' agility and responsiveness to consumer needs;

(2) Acknowledge the role that human capital plays in fostering innovation. Invest in initiatives for training and development to upskill and keep skilled staff members. Encourage a culture of exploration and creativity where staff members are encouraged to share their ideas.

(3) Direct financial resources toward R&D projects more effectively. For creative ventures, think about collaborating with venture capitalists or private investors to obtain extra money. Make sure that financial rewards promote risk-taking and are in line with innovation objectives.

(4) Take note of the innovative tactics that NSOEs have found to be successful. To find areas where SOEs may enhance their operations, examine their personnel management procedures, organizational structures, and decision-making procedures.

From a broader national perspective, the United States and the European Union boast elite R&D teams and sophisticated innovation systems, exhibiting a pronounced advantage in the quality and the accelerating growth rate of their innovative outputs. China, while making remarkable progress in the realm of innovation against the backdrop of global competition, remains committed to bridging the gap with industrialized nations in scientific and technological advancement. Enhancing a nation's innovative prowess fundamentally mirrors the enhancement of corporate innovation, necessitating strategic investments in both financial resources and human capital. It is envisioned that China, by consistently optimizing the efficiency of capital utilization and refining the management strategies for its creative workforce, will emerge as a forerunner in global science and technology innovation.

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## References

Arocena, P., & Diana O., 2012. The Efficiency of State-Owned and Privatized Firms: Does Ownership Make a Difference? *International Journal of Production Economics*, 140(1), 457–465.

Bai, C.E., David D., Li, Z.T., & Wang, Y. J., 2000. A Multitask Theory of State Enterprise Reform. *Journal of Comparative Economics*, 28(4), 716–738.

Butler, J. E., 1988. Theories of Technological Innovation as Useful Tools for Corporate Strategy. *Strategic Management Journal* , 9(1), 15–29.

Cao, X.P., Douglas C., & Zhou, S.L., 2020. State Ownership and Corporate Innovative Efficiency. *Emerging Markets Review*, 44,100699.

Castellacci, F., & Christine, M.L., 2015. Do the Effects of R&D Tax Credits Vary across Industries? A Meta-Regression Analysis. *Research Policy*, 44(4),819–832.

Chang, Y., Wang, X.C., & Annie, P. C., 2019. Solving the Innovation Problem in State-Owned Firms: The Role of Entrepreneurial Orientation and High-Commitment HR Practices. *Industrial Marketing Management*, 83, 239–250.

Chen, C.P., Hu, J.L., &Yang, C.H., 2011. An International Comparison of R&D Efficiency of Multiple Innovative Outputs: The Role of the National Innovation System. *Innovation*, 13(3), 341–360.

Chen,L., & Yang, W.H., 2019. "R&D Tax Credits and Firm Innovation: Evidence from China." *Technological Forecasting and Social Change*, 146,233–241.

Chen, S., Z. Sun, S. Tang, & D. Wu., 2011. Government Intervention and Investment Efficiency: Evidence from China. *Journal of Corporate Finance*, 17(2), 259–271.

Cruz-Cázares, Claudio, Bayona-Sáez, C. & T. García-Marco.,2013. You Can't Manage Right What You Can't Measure Well: Technological Innovation Efficiency. *Research Policy*, 42(6–7), 1239–1250.

Cumming, D., O. Rui, & Y. Wu., 2016. Political Instability, Access to Private Debt, and Innovation Investment in China. *Emerging Markets Review*, 29, 68–81.

Dong, Y., Q. Hou, & C. Ni., 2021. Implicit Government Guarantees and Credit Ratings. *Journal of Corporate Finance*, 69, 102046.

Fiorentino, R., S. Longobardi, & A. Scaletti., 2020. The Early Growth of Start-Ups: Innovation Matters. Evidence from Italy. *European Journal of Innovation Management*, 24(5), 1525–1546.

Fredrickson, J. W., A. Davis-Blake, & W. M. Gerard Sanders.,2010. Sharing the Wealth: Social Comparisons and Pay Dispersion in the CEO's Top Team. *Strategic Management Journal*, 31(10), 1031–1253.

Hao, J. ,2023. Retail Investor Attention and Corporate Innovation in the Big Data Era. *International Review of Financial Analysis*, 86, 102486.

Hirshleifer, D., P. H. Hsu, & D. Li. ,2013. Innovative Efficiency and Stock Returns. *Journal of Financial Economics*, 107(3), 632–54.

Holmstrom, B., 1989. Agency Costs and Innovation. *Journal of Economic Behavior & Organization*, 12(3), 305–327.

Jiancheng Guan & K. Chen. ,2012. Modeling the relative efficiency of national innovation systems. *Research Policy*, 41(1), 102–115.

Kato, M., H. Okamuro, & Y. Honjo., 2015. Does Founders' Human Capital Matter for Innovation? Evidence from Japanese Start-Ups. *Journal of Small Business Management*, 53(1), 114–128.

Lane, J., H. G. Broadman, & I. Singh., 1998. Labor Flexibility, Ownership and Firm Performance in China. *Review of Industrial Organization*, 13(6), 621–635.

Li, H. C., W. C. Lee, & B. T. Ko. ,2017. What Determines Misallocation in Innovation? A Study of Regional Innovation in China. *Journal of Macroeconomics*, 52, 221–237.

Lin, J. Y. F., F. Cai, & Z. Li., 1998. Competition, Policy Burdens, and State-Owned Enterprise Reform. *The American Economic Review*, 88(2), 422–427.

Ling, Y., Z. Simsek, M. H. Lubatkin, & J. F. Veiga., 2008. Transformational Leadership's Role in Promoting Corporate Entrepreneurship: Examining the CEO-TMT Interface. *Academy of Management Journal*, 51(3), 557–576.

Liu, D., Y. Gong, J. Zhou, & J. C. Huang., 2017. Human Resource Systems, Employee Creativity, and Firm Innovation: The Moderating Role of Firm Ownership. *Academy of Management Journal*, 60(3), 1164–1188.

Lou, Z., C. Wang, Y. Liu, & J. Xu., 2023. It Takes Two to Tango: Impact of Salary Co-Movement between Top Executives and Ordinary Employees on Corporate Innovation. *Finance Research Letters*, 55, 103935.

Maskin, E., & C. Xu., 2001. Soft Budget Constraint Theories: From Centralization to the Market. *Economics of Transition*, 9(1), 1–27.

Ongsakul, V., P. Chatjuthamard, & P. Jiraporn., 2022. Does the Market for Corporate Control Impede or Promote Corporate Innovation Efficiency? Evidence from Research Quotient. *Finance Research Letters*, 46, 102212.

O'Regan, N., A. Ghobadian, & D. Gallear. ,2006. In Search of the Drivers of High Growth in Manufacturing SMEs. *Technovation*, 26(1), 30–41.

Piao, Z., B. Miao, Z. Zheng, & F. Xu., 2022. Technological Innovation Efficiency and Its Impact Factors: An Investigation of China's Listed Energy Companies. *Energy Economics*, 112, 106140.

Qian, Y., & C. Xu., 1998. Innovation and Bureaucracy Under Soft and Hard Budget Constraints. *The Review of Economic Studies*, 65(1), 151–164.

Qiao, S., D. H. Zhao, Z. X. Guo, & Z. Tao., 2022. Factor Price Distortions, Environmental Regulation and Innovation Efficiency: An Empirical Study on China's Power Enterprises. *Energy Policy*, 164, 112887.

Rawski, T. G. ,1997. Who Has Soft Budget Constraints? *Global Economic Review*, 26(1), 29–49.

Romer, P. M. 1990. Endogenous Technological Change. *Journal of Political Economy*, 98(5, Part 2), 71–102.

Sen Qiao, H. H. Chen, & R. R. Zhang., 2021. Examining the Impact of Factor Price Distortions and Social Welfare on Innovation Efficiency from the Microdata of Chinese Renewable Energy Industry. *Renewable and Sustainable Energy Reviews*, 143, 110901.

Shin, J., Y. J. Kim, S. Jung, & C. Kim., 2022. Product and Service Innovation: Comparison between Performance and Efficiency.

*Journal of Innovation & Knowledge*, 7(3), 100191.

Souitaris, V. ,2002. Technological Trajectories as Moderators of Firm-Level Determinants of Innovation. *Research Policy*, 31(6), 877–898.

Walheer, B., & M. He., 2020., Technical Efficiency and Technology Gap of the Manufacturing Industry in China: Does Firm Ownership Matter? *World Development*, 127, 104769.

Zhang, A., Y. Zhang, & R. Zhao., 2003. A Study of the R&D Efficiency and Productivity of Chinese Firms. *Journal of Comparative Economics*, 31(3), 444–464.

Yang, Z., S. Shao, C. Li, & L. Yang., 2020. Alleviating the Misallocation of R&D Inputs in China's Manufacturing Sector: From the Perspectives of Factor-Biased Technological Innovation and Substitution Elasticity. *Technological Forecasting and Social Change*, 151, 119878.

Zhong, K., C. Li, & Q. Wang., 2021. Evaluation of Bank Innovation Efficiency with Data Envelopment Analysis: From the Perspective of Uncovering the Black Box between Input and Output.*Mathematics*, 9(24), 3318.