Does External Monitoring from Government Improve the Performance of State-Owned Enterprises?*

Short title: External Monitoring and SOE Performance

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Abstract

This paper investigates the impact of external monitoring from government on SOE performance, using variation in monitoring strength arising from a nationwide policy change and firms' geographic location in China. We utilize a structural approach to estimate input prices and productivity separately at the firm level using commonly available production data. We show that enhanced external monitoring, as a key component of corporate governance, can substantially reduce managerial expropriation in procurement (proxied by input prices) and shirking in production management (proxied by productivity). The results suggest that government monitoring can be an effective policy instrument to improve SOE performance.

Keywords: *productivity, input prices, external monitoring, SOE performance, production function estimation*

JEL classification: *D2, L11, O38*

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1 Introduction

Effective external monitoring of firm management—by investors, debtors, or the supervising government—is an indispensable component in corporate governance to reduce managerial expropriation and shirking (e.g., Becker, 1968; Allingham and Sandmo, 1972). State-owned enterprises (SOEs), while playing an important role in the global economy and accounting for 24% of sales in the Fortune Global 500 in 2014, have been renowned for ineffective external monitoring of their management. This is largely due to their property rights arrangement and weak legal enforcement arising from strong political connections, especially in developing countries. While previous work analyzing the performance of SOEs emphasizes *internal* incentivization (e.g., Groves et al., 1994; Li, 1997; Konings et al., 2005; Brown et al., 2006; Estrin et al., 2009; Chen et al., 2017), the impact of *external* monitoring has been largely ignored.

This paper empirically examines the role of external monitoring from government in SOE performance. We distinguish the impact of external monitoring on managerial expropriation in procurement and shirking in production management. Facing weaker external monitoring, SOE managers are more likely to be corrupt in material procurement compared with their private counterparts, for example, by taking kickbacks, self-dealing, and engaging in secret transactions with relational firms. This directly increases the material input prices paid by SOEs and consequently reduces profits. Beyond that, ineffective external monitoring may result in lower productivity, because it can increase managerial shirking directly, or indirectly if (higher) productivity and (lower) input prices are complementary in promoting profits. The Annual Surveys of Industrial Production (1998-2007) in China provide an excellent background to examine these issues. After suffering from ineffective external monitoring for a long time, Chinese SOEs experienced strengthened monitoring from government due to a significant nationwide policy change. Moreover, the size of the country and the geographic diversity of firms generate large variations in monitoring strength faced by SOEs in different locations.

This paper utilizes the variation in the strength of government monitoring arising from the nationwide policy change and firms' geographic location to investigate the impact of external monitoring on SOE performance in input prices and productivity, using a difference-in-differences style analysis. One challenge is that our dataset, like many other production survey datasets, does not include firm-level input prices or productivity. To address this issue, we estimate firm-level measures of input prices and productivity using the structural approach of production function estimation initially developed in Grieco et al. (2016) and extended in Grieco et al. (2019). This provides a methodologically feasible approach to overcome the common data limitation in the literature on firm performance. The central idea is to use firms' optimality conditions on input choices together with information on wages and input expenditures to infer and control for material input prices in the estimation of the production function. This approach contrasts with the traditional practice in a large number of studies on firm performance (e.g., Brandt et al., 2012; Chen et al., 2017; Berkowitz et al., 2017), which estimate total factor productivity (TFP) without accounting for firm heterogeneity in material prices.[1] Our approach also allows for capital market distortions/mis-allocations, difference in firm productivity management, and corruption in input procurement, which is a crucial feature in the comparison of performance across firms (especially between SOEs and non-SOEs).

Applying the analysis to the Annual Survey of Industrial Production in China, we document the weak performance of SOEs in productivity and in the ability to secure better input prices. The productivity of SOEs is about 20% lower and they face 6.4% higher input prices compared with their private counterparts on average, after controlling for observable characteristics such as size, industry, and location. This is despite SOEs' privileges in input and output markets, market power, and bargaining power to access discounted input prices, arising from their connections to government. The higher input prices, as a result, are consistent with the existence of serious corruption and/or shirking in the material procurement process. Because material expenditure accounts for over 80% of total variable costs in Chinese manufacturing industries, the impact of such overpayment on materials is substantial: it leads to about a 5.1% loss in profits for SOEs.

To explore the causality and circumvent other confounding factors, we first use a before-and-after analysis and investigate how time-variation in the strength of external monitoring affects SOE performance. Specifically, we examine the effect of the *State-owned Assets Supervision and Administration Commission* (SASAC) on SOE performance in China. SASAC was established in 2003 as the legal owner of state-owned assets under the leadership of the State Council. It directly enhanced external monitoring of the management of SOEs nationwide, by a combination of measures such as designating a board of supervisors and imposing more accurate performance evaluation for top executives.[2] Because SASAC only affects SOEs but not private firms, it naturally serves as a quasi-experiment to identify the impact of improved external monitoring by comparing the changes in the performance of these two types of firms. In the data, we observe a quick catch-up of SOEs' profitability compared with that of non-SOEs after the establishment of SASAC, as is documented in Hsieh and Song (2015). Notably, this catch-up is mainly driven by the improved performance of SOEs. Consistently, our results show that SASAC

[1] Their estimation is based on the production function estimation frameworks of Olley and Pakes (1996), Levinsohn and Petrin (2003), De Loecker and Warzynski (2012), Ackerberg et al. (2015), and Gandhi et al. (2020). In practice, these frameworks assume homogeneous material prices to use deflated material expenditure as a proxy for input quantity when estimating productivity. However, recent studies have shown large heterogeneity in input prices across firms (Ornaghi, 2006; Atalay, 2014), and productivity estimation may be biased if the heterogeneity of input prices is correlated with the choice of inputs and ignored (Grieco et al., 2016; De Loecker et al., 2016; Brandt et al., 2017).

[2] In addition, SASAC reinforced legal procedures for punishing corrupt executives of SOEs. Gong and Wu (2012) summarize the court cases on corruption that involved government officials and top executives in SOEs, based on reporting in China's official news, Procuratorial Daily. They found the average annual number of court cases increased from 235 before (and during) 2003 to 333 after 2003. Given that these types of cases usually involved misconduct years before the trials, the increase reflects enhanced external monitoring and legal punishment strength after 2003.

reduced the input prices paid by SOEs by 3.9%, closing the gap between SOEs and non-SOEs by half. The establishment of SASAC also increased the productivity of SOEs by 12.6% relative to their private counterparts, closing the gap by about 53%.

We next exploit the spatial variation in monitoring costs and evaluate how it influences SOE performance. Higher costs of external monitoring reduce monitoring strength and consequently lead to more managerial expropriation and shirking. Because monitoring costs are unobservable, we proxy them using SOEs' direct spherical physical distance to their oversight government agency, following Huang et al. (forthcoming).[3] Intuitively, greater distance increases information asymmetry and monitoring difficulties, leading to higher monitoring costs. A possible concern is that such proxy may confound other firm performance drivers, such as agglomeration and localization. Fortunately, non-SOEs are also registered with the government similarly, and their distance to their affiliated government can be calculated in the same way. However, the government bears no responsibility for monitoring non-SOEs. This difference helps to identify the effect of distance as a proxy for monitoring costs from its effect as a factor of agglomeration and localization. In our empirical analysis, we find that SOEs at greater distances to their oversight government pay higher input prices and have lower productivity: doubling the oversight distance on average increases SOEs' input prices by 0.3% and reduces their productivity by 0.7%, relative to non-SOEs.

Interestingly, as a reinforcement for monitoring SOEs, SASAC largely alleviates such negative influence of oversight distance on SOE performance. It reduces the performance gaps in terms of input prices and productivity between SOEs that are far from their oversight government and those that are close. This could arise because of the larger potential gains for SOEs that are farther from their oversight government (i.e., weaker monitoring before SASAC), or because SASAC might have implemented a higher order of monitoring of those SOEs that were farther away. Both reasons contribute to the heterogeneous impact of SASAC's external monitoring on SOE performance. When using the traditional TFP measure without separating input price heterogeneity from productivity, we find a qualitatively similar result, echoing Sheng and Liu (2016) who show that SASAC increases SOE firms' TFP, profitability, and sales.

To explore the mechanism that makes oversight distance matter, we analyze how travel difficulty — the ratio of the shortest road distance to the direct spherical distance between SOEs and their affiliated governments — affects SOE performance. Travel difficulty captures the travel costs arising from geographic landscape and road infrastructure development, given the direct distance. We find that travel difficulty has a negative and significant impact on SOEs' input prices and productivity

[3]In China, SOEs and non-SOEs, by registration, are affiliated to one of the following government levels: central, province, or municipality (or prefecture). The difference is that the affiliated governments bear the responsibility for overseeing SOEs but not non-SOEs.

relative to non-SOEs. This suggests that the physical interaction of government officials with SOEs is a mechanism that makes oversight distance matter. As an alternative strategy, we control for SOEs' distance to the largest city other than the city of the oversight government in the area. The non-oversight distance helps to control for spatial-related factors such as agglomeration and localized material prices (other than monitoring costs) that may influence firm performance. Therefore, the differential effect of the oversight distance and non-oversight distance identifies the effect of monitoring costs arising from oversight distance. The strong differential effect reflects that the distance-related monitoring costs matter for SOE performance. The SASAC effect is also robust in this case.

Overall, external monitoring, by affecting input prices and productivity, has substantial impact on the aggregate performance of SOEs as well as the entire manufacturing sector. In our accounting analysis, the costs of monitoring SOEs due to geographic distance raise the aggregate input price by 1.09% and reduce the aggregate productivity by 2.61% within the group of SOEs. This translates into an increase in input prices by 0.16% and a loss of productivity by 0.42% for the manufacturing sector. SASAC, as an SOE-exclusive policy, significantly reduced the aggregate input price by 4.03% and increased aggregate productivity by 10.97% for SOEs relative to non-SOEs. As a result, the aggregate input price for the entire manufacturing sector was reduced by 0.56% and aggregate productivity was increased by 1.46%.

We conduct a wide range of analyses to secure our results from other potential driving forces, such as privatization, improvement of market competition, and possible enhancement of privilege and internal incentives for SOEs that came along with SASAC. Our results are also robust after controlling for the potential differential trends between SOEs and non-SOEs, using a balanced panel, adopting an alternative definition of SOEs following Hsieh and Song (2015), and controlling for firm fixed effects, China's accession to the World Trade Organization (WTO), and firms' trade participation.

Our paper complements two recent studies. Hsieh and Song (2015) emphasize the role of restructuring in improving SOE performance: large SOEs were corporatized and merged into large industrial groups under the control of the Chinese state and small SOEs were privatized or closed. Berkowitz et al. (2017) focus on the role of capital market distortion and the reduction of excess labor in driving up SOE profitability. In contrast, our paper identifies external monitoring from government as a new and important driving force of SOE performance in affecting managerial expropriation in procurement and shirking in production management. Importantly, the results of the monitoring effect are robust after controlling for SOE restructuring, capital market distortion, and reduction of excess labor in SOEs.

By focusing on external monitoring, this paper contributes to the literature on the performance of SOEs, which documents significant gaps between Chinese state-owned and private manufacturing firms in profitability, TFP, and capital productivity (e.g., Jefferson and Rawski, 1994; Xu, 2011; Brandt et al., 2012). Meanwhile, a large literature, emphasizing changes inside firms, attributes the catch-up of Chinese SOEs to privatization and incentivization reforms (i.e., Groves et al., 1994; Li, 1997; D'Souza et al., 2005; Estrin et al., 2009; Xu, 2011; Chen et al., 2017). Complementing this literature, our results suggest that strengthening external monitoring of firms to improve SOE performance can be an effective alternative policy to privatization and incentive schemes. This finding has practical policy implications for SOE reforms, especially in developing countries and industries where state ownership must be maintained due to economic or political reasons.

This paper is also related to the literature on the impact of monitoring/sanction in corporate governance. Although the corporate governance theory has long recognized the importance of effective monitoring of firm performance, its effect on agent behavior is mixed in the literature. The traditional agency theory suggests that a self-interested agent will work harder and engage less in expropriation to reduce the probability of a sanction (Alchian and Demsetz, 1972; Calvo and Wellisz, 1978; Fama and Jensen, 1983; Laffont and Martimort, 2002). In contrast, the "crowding-out" theory in behavioral economics predicts that increased monitoring may reduce effort, because the induced distrust violates the norm of reciprocity (Frey, 1993). Overall, the empirical literature, mainly based on experiments, shows mixed evidence (e.g., Nagin et al., 2002; Dickinson and Villeval, 2008). Our paper uses a nationwide quasi-natural experiment in Chinese manufacturing industries and finds a strong positive impact of monitoring on firm performance via the channels of input prices and productivity.

The rest of the paper is organized as follows. Section 2 provides the economic background of Chinese SOE reform and external monitoring. Section 3 describes the data and estimates the key measures of material prices and productivity via a structural approach, which will be used in the empirical study of firm performance. Section 4 conducts the main empirical study by investigating the role of external monitoring from the time and spatial dimensions. We conclude in Section 5.

2 Economic Background

2.1 SOE Reform and External Monitoring before SASAC

Chinese SOEs have undergone three phases of reform since 1978. The first phase (1978-1984) focused on management reform, with an attempt to increase economic incentives for SOEs by giving them greater autonomy and allowing them to keep a proportion of their profits. The second phase (1984-1992) was market-oriented, introducing market competition in the economy. The traditional administrative relationship between SOEs and government was replaced by a contractual relationship during this period. The third phase (1993-present) focused on ownership reform via privatization and the introduction of the modern enterprise system. Many SOEs were privatized by introducing private investors. Even after years of privatization, SOEs still played an important role in the Chinese economy. For example, in 2003, SOEs accounted for 56% of total assets in manufacturing industries and provided 38% of manufacturing employment. Overall, through these reforms, the responsibility for output decisions was shifted from the state to firms (Xu, 2011), and the profit objective of the SOEs and non-SOEs was more aligned than ever.[4] In particular, SOEs were allowed to retain all their profits starting from 1994 (until 2007), which gave them stronger incentives to maximize profits than previously.

Despite the waves of reform, the problem of external monitoring of SOEs remained. This was fundamentally because SOEs did not have clearly assigned property rights: by constitution they are "owned by all the people" in the country. Each person in the economy only has a tiny share of ownership and this ownership is nominal because individuals cannot claim dividends from SOEs directly. Thus, no one has an incentive to monitor SOEs. Government, as the nominal investor representing all the people, was supposed to supervise and monitor SOEs. But before 2003, the government's external monitoring was very weak. First, not being the final owners and residual keepers, the government officers in charge did not have a strong incentive to monitor SOEs. Even worse, multiple government departments collectively supervised the same SOEs. These departments usually shirked responsibility among each other and eventually no one took real responsibility for the losses of SOEs. In addition, China had a relatively low requirement for information disclosure even for listed firms during the data period. As a result, there was serious information asymmetry between firms and the government, which exacerbated the problem due to the large costs of monitoring SOEs, especially in remote areas.

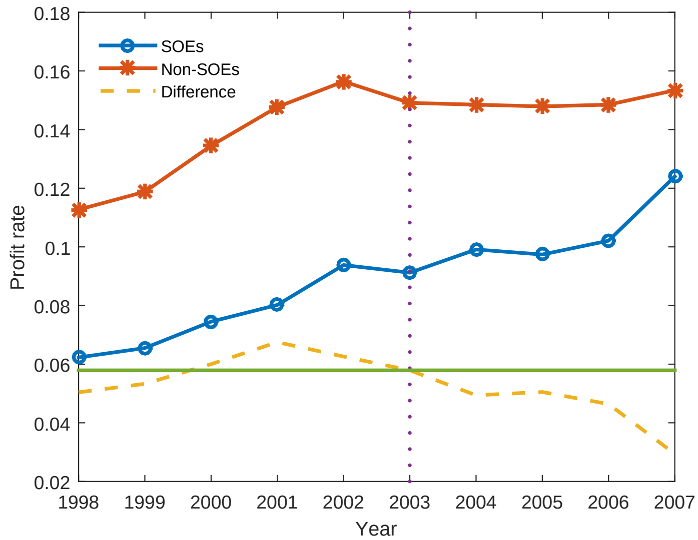
Without effective monitoring, SOE managers had almost ultimate control over the firm's production and transactions. Such a de facto serious insider control problem in corporate governance facilitates managerial expropriation and shirking. First, corruption and kickbacks were common when SOEs purchased products and services (Cheng, 2004). It was almost a norm that SOE managers took a certain percentage of the transaction price as a kickback from procurement bidders or intermediate material suppliers. Second, it was also common for SOE managers to conduct self-dealing and relational transactions. For example, SOE managers may purchase intermediate materials from private firms owned by their family members or close business partners/friends who charge prices that are higher than market prices. In such way, SOE managers can "expropriate" state-owned assets and transfer them to their own pockets. Moreover, facing weak monitoring, SOE mangers might shirk in bargaining for better material prices in the input market.[5] These issues drove up the material prices paid by SOEs.

[4] Of course, SOEs and non-SOEs might still face different labor market frictions. We discuss the potential impact of labor market friction and the robustness of our results to it at the end of Section 4.3.1.

[5] Instead, they had a strong incentive to pursue perquisite consumption, such as luxury wines, liquors, and cigarettes, which were usually recorded illegally as intermediate inputs expenditure. A piece of evidence is the example of Moutai, which is the number one luxury liquor brand in China and a popular corruption consumption good. After President Xi Jinping launched his Anti-corruption Campaign at the end of 2012, which affected the government and SOEs, the stock price of Moutai dropped over 50% in 14 months, from November 2012 to January 2014. In contrast, over the same period, the Shanghai Stock Exchange Composite Index remained almost unchanged.

Similarly, weak external monitoring of SOEs may cause managerial shirking in production. Overall, these problems echo the SOEs' underperformance in profitability: the average profit rate of SOEs in the manufacturing industries was consistently about 6 percentage points lower than that of non-SOEs during 1998 to 2003, as shown in Figure 1.

Figure 1: *Average profit rate of SOEs and non-SOEs in Chinese manufacturering industries*



Note: The average profit rate is calculated as the revenue-weighted average for a balanced panel of Chinese manufacturing firms during 1998-2007. The pattern is similar for the median profit rate.

2.2 External Monitoring after SASAC

To strengthen monitoring and management of SOEs, the State Council of China announced the establishment of SASAC in March 2003 as the legal owner of state-owned assets. Its hierarchy consists of central, provincial, and prefecture-level SASAC offices. The central SASAC was established in March 2003; the provincial and prefecture-level SASAC offices were established later. In particular, provincial SASAC offices were set up in all 31 provinces (including autonomous regions and municipalities directly controlled by the central government) by early 2004. Since then, SASAC has become the single most powerful government department that takes full responsibility for the performance of SOEs, solving the problem of government monitoring of SOEs, as before SASAC multiple government departments together monitored the same SOE. Specifically, each SOE is supervised by one of the SASAC offices, depending on the level of its oversight government: the central SASAC mainly supervises the central SOEs and local SASACs supervise local SOEs.

Upon the establishment of SASAC, the State Council announced a series of policies and regulations on the practice of SASAC nationally, which clarified the roles of SASAC and its measures used to manage SOEs (i.e., *Policies, Laws & Regulations: Decree of the State Council of the People's Republic of China.*

No. 378 effective in 2003). The main functions of SASAC are to perform investors' responsibilities, supervise SOEs, and monitor state-owned assets. It took several specific and complementary measures to achieve these goals. First, SASAC improved the assessment criteria and index system to ensure the preservation and growth of state-owned assets. Based on this system, SASAC uses statistics and auditing to implement effective monitoring of SOEs. Second, SASAC helps SOEs to establish a modern enterprise system to improve corporate governance. Third, SASAC is responsible for appointing, evaluating, and removing top executives of SOEs based on their performance. Fourth, SASAC dispatches supervisory panels, which report to SASAC directly, to the supervised SOEs to monitor their daily management. Finally, SASAC participates in formulating the operational budgets and final accounts of SOEs. It is also responsible for ensuring that SOEs turn over their capital gains to the state. More details on SASAC monitoring are provided in Online Appendix A.

These strong monitoring actions yielded fruitful outcomes.[6] During 2004 to 2008, SASAC initiated 77,081 supervision and monitoring projects in SOEs on business operations and transactions, which saved over 28 billion RMB (US$3.5 billion) for SOEs; identified 3.69 billion RMB (US$ 0.46 billion) of corrupt money; and recovered economic losses of more than 7.78 billion RMB (US$ 0.97 billion). The strengthened monitoring is particularly effective at the local level, given the weak monitoring faced by local SOEs before SASAC. For example, in 2004, the province-level SASAC in *Hei Long Jiang* investigated 499 cases that violated the law and punished 702 SOE managers and government officials associated with corruption, recovering economic losses of 76 million RMB (US$ 9.5 million). In 2005, the city-level SASAC in *Qing Dao* investigated and audited 1,152 SOEs, identifying 7,324 accounting errors. Overall, the measures taken by SASAC directly strengthened the external monitoring of SOEs. Figure 1 shows that the gap in the average profit rate between SOEs and non-SOEs narrowed significantly after SASAC was established. From 2003 to 2004, the gap reduced by about 1 percentage point (from 6% to 5%), and it continued to shrink to 3% in 2007. The narrowing of the gap was mainly driven by the improved performance of SOEs after 2003.

For the purpose of our empirical analysis, several important features of SASAC stand out. First, SASAC only directly affects SOEs. Second, as the single government agency responsible for the management and supervision of SOEs, it took full responsibility for the performance of SOEs. This is in sharp contrast to the situation before 2003, when multiple government departments were responsible for supervising the same SOEs and none took responsibility for the losses of SOEs. Third, SASAC itself is directly led and supervised by the State Council and Central Discipline Inspection Commission. The latter is a special agency supervised by the central government and responsible for auditing and detecting misbehavior and corruption of government officials and SOE managers. The Central

[6] Sourced from the official SASAC website (accessed August 31, 2019) http://www.sasac.gov.cn/2008rdzt/2008rdzt_0003/gzw5zn0311.htm and http://www.sasac.gov.cn/n2588020/n2877928/n2878219/c3748582/content.html.

Discipline Inspection Commission has a special team residing in SASAC to reduce the possibility of corruption of SASAC itself. These features, together with detailed measures undertaken by SASAC, increased the economic and legal costs of opportunism among SOE managers, and consequently reduced the incentives for managerial expropriation and shirking. In sum, SASAC provides a sharp, nationwide quasi-experiment policy change to identify the impact of strengthened monitoring on SOE performance.

2.3 Besides SASAC: A Map of SOE Reforms during the Data Period

Although the establishment of SASAC was the biggest SOE policy initiative during the data period, it was not the only one. First, privatization of SOEs, which started in 1992, was still in effect, and it was reinforced in 1996 following the guideline of "grasp the large and let go of the small." Many SOEs were privatized during the data period. Second, in the Fourth Plenary Session of the 15th Central Committee of the Communist Party in September 1999, the central government formed 10 guidelines for SOE reform and development. The guidelines emphasize the integration of privatization, monitoring, market competition, and the establishment of a modern enterprise system to improve SOE performance. These policies may improve internal monitoring and incentives due to improved corporate governance, in addition to external monitoring. Moreover, the Chinese government gradually reduced the barriers for private firms to enter many industries, including those in which SOEs have monopoly power, to meet the WTO requirement and increase the viability of Chinese firms after joining the WTO. Overall, these policies were initiated earlier and progressed relatively smoothly during the data period, in contrast to the striking improvement in SOE performance that was concurrent with the establishment of SASAC. In Online Appendix G, we discuss the impact of these policies in detail and show that they are unlikely to drive our main results.

3 Data and Estimation

3.1 Data and Summary Statistics

The data used in the analysis were drawn from the Chinese Annual Surveys of Industrial Production, which are collected annually by the National Bureau of Statistics in China. The data cover non-state-owned firms with annual sales greater than five million RMB (or equivalently about US$600,000) and *all* state-owned firms during 1998-2007. The surveys record detailed firm-level information on total sales, number of workers, wage expenditure, material expenditure, book value of capital stock, and so forth. But the data do not provide information on material prices or quantities. In total, the dataset contains 326,294 firms across 19 major two-digit Standard Industrial Classification (SIC) manufacturing industries.

Following Huang et al. (forthcoming) and many others, we define a firm as an SOE if it has a share of state ownership over 30%.[7] This definition yields 39,444 SOEs. We call the other firms non-SOEs, as they essentially consist of firms whose main ownership is individual, corporate, foreign, or collective. As several papers have noted (e.g., Hsieh and Song, 2015; Chen et al., 2017; Berkowitz et al., 2017), many SOEs were privatized in the data period. Although privatization may improve monitoring in general, it also involves radical changes of the firm in many other aspects (e.g., internal restructuring and incentivization), which cannot be identified from the change in monitoring from the available data. Thus, this paper does not explore the impact of privatization; instead, we show in Online Appendix G that our results on the causality between monitoring and firm performance are robust to a subsample that excludes these privatized firms.

Table 1: *Summary Statistics of Chinese Manufacturing Industries*

Statistics	SOEs	Non-SOEs
Total Sales (Median)	1.648	2.143
Material Expenditure (Median)	1.221	1.665
Capital Stock (Median)	1.316	0.439
Wage Expenditure (Median)	0.212	0.146
Material Share over Total Variable Cost (Median)	0.795	0.903
Number of Firms	39,444	286,850

[1] All monetary values in this table are in millions of 2000 U.S. dollars.

[2] Total Variable Cost uses a 5% interest rate as cost for capital.

Several important facts emerge from the summary statistics in Table 1. First, compared with non-SOEs, SOEs are significantly larger in capital stock and number of workers. SOEs possess three times the capital stock and almost twice the work force as non-SOEs do on average. Given that larger firms usually have greater market power in the input and output markets, these findings suggest that controlling firm size is necessary for comparing the two groups. Second, materials expenditure accounts for a substantial share of total variable cost. This feature is shared by both types of firms. In particular, the material expenditure of SOEs is more than five times their costs for labor. As a result, our focus on the impact of external monitoring through the material price channel is of particular importance: saving of one percentage point in the material price increases profitability more than saving of five percentage points in labor does, even without considering substitution between labor and material. Previous literature focuses on the role of labor input in explaining the weak performance of SOEs (e.g., Bai et al., 2006; Berkowitz et al., 2017). In contrast, we study how the inferior performance of SOEs can be attributed to the lack of effective external monitoring, which results in higher material input prices, presumably due to managerial expropriation and shirking.

[7] Alternatively, SOEs could be defined using a different cutoff point, or using the firm's registration ownership type. We show in Online Appendix G.9 that the results are robust to alternative definitions of SOEs.

3.2 Structural Approach

The strength of external monitoring can influence a firm's profitability by affecting its input prices and productivity. To see this, consider a stylized model where a firm makes two layers of decisions sequentially: first by a top manager and then by a production unit.[8] The top manager chooses her efforts, which determine input prices and productivity. Observing the input prices and productivity, the production unit then chooses quantities of labor and material to maximize firm profit. The top manager is self-interested and her choices are made to maximize her own payoff: her share of the firm profit (performance payment) plus the kickback in material procurement, net of the costs of exerting the effort and the expected punishment for taking kickbacks. Distortions in input prices and productivity may arise from the decisions of the self-interested top managers balancing the trade-off between the performance payment and the net payment from taking the kickback, on which external monitoring can have an impact. A direct conjecture is that: stronger external monitoring increases effort in material procurement and production management, resulting in lower material input prices and higher productivity.

Nonetheless, our dataset, like many other production survey datasets, does not include firm-level material prices. This places a challenge in the estimation of productivity as a well-recognized measure of firm performance: production function estimation (thus, the resulting productivity measure) is biased if the heterogeneity of unobserved input prices is correlated with the choice of inputs and ignored (Grieco et al., 2016; De Loecker et al., 2016; Brandt et al., 2017). This subsection introduces a stylized model to estimate the quality-adjusted input prices and productivity separately using commonly available datasets, based on Grieco et al. (2016, 2019). Obtaining such an input price measure is important for our analysis: to identify the effect of external monitoring, a fair comparison of firm input prices should consider firms' fundamental ability to access lower prices conditional on their choices of input quality.

3.2.1 Setup

In an industry, each firm j in period t produces output (Q_{jt}) of quality Φ_{jt}. The output quality depends on the firms' intrinsic productivity and their choice of input quality. We assume that goods of higher quality boost demand and so quality-inclusive output is $\tilde{Q}_{jt} = \Phi_{jt} Q_{jt}$.[9] Firms are monopolistically competitive and face a constant elasticity of substitution (CES) demand function:

$$P_{jt} = (\Phi_{jt} Q_{jt})^{1/\eta} = \left(\tilde{Q}_{jt}\right)^{1/\eta}, \tag{1}$$

[8] Online Appendix C provides detailed analysis based on a stylized model of managers' effort decisions, while the main task of the paper is to test the implied conjectures.

[9] We use $\tilde{X}$ to denote variables that are quality-inclusive throughout this paper.

where P_{jt} is the output price and η is the demand elasticity. The quality-inclusive output is produced using a gross CES production function using labor (L_{jt}), material (M_{jt}), and capital (K_{jt}) as inputs:

$$\tilde{Q}_{jt} = \tilde{\Omega}_{jt} F(L_{jt}, M_{jt}, K_{jt}) = \tilde{\Omega}_{jt} \left[\alpha_L L_{jt}^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma}\right]^{\frac{1}{\gamma}}, \tag{2}$$

where $\alpha_L, \alpha_M, \alpha_K$ are the distribution parameters, which sum up to one by normalization. The elasticity of substitution among inputs (σ) is determined by γ, where $\gamma = (\sigma - 1)/\sigma$. Since we observe output revenue but not the output quantity or prices in our data, we emphasize that we can only recover revenue-based productivity. Specifically, the Hicks-neutral $\tilde{\Omega}$ captures the combination of output-productivity and output-quality heterogeneity at the firm level.[10]

Our goal is to estimate measures of input prices and productivity that are comparable across firms. This amounts to separating the impact of input price and quality dispersion from other potential sources of productivity differences across firms. This approach acknowledges the findings of Kugler and Verhoogen (2009, 2012) and others, which show that higher productivity firms tend to use higher quality inputs. De Loecker et al. (2016) posit the same relationship between productivity, input quality, and output quality to motivate the use of output prices as proxies for input prices. In light of this, we assume that $\tilde{\Omega}_{jt}$ is a function of the firms' underlying productivity, Ω_{jt}, and its endogenous choice of input quality, H_{jt}. We adopt a functional form that allows productivity and input quality to be either substitutes or complements:[11]

$$\tilde{\Omega}_{jt} = \left[\Omega_{jt}^{\theta} + H_{jt}^{\theta}\right]^{\frac{1}{\theta}}, \theta \neq 0. \tag{3}$$

The elasticity of substitution between productivity and input quality is measured as $1/(1-\theta)$: if $\theta < 0$, then productivity and input quality are gross complements of each other. Over time, productivity $\omega_{jt} \equiv \ln \Omega_{jt}$ evolves according to an AR(1) process:

$$\omega_{jt+1} = f_0 + f_{soe} SOE_{jt} + f_{SASAC} SASAC_t + f_1 \omega_{jt} + \epsilon^{\omega}_{jt+1}, \tag{4}$$

[10] Our model considers the effect of material quality through the input-output quality linkage only. However, material quality may also have an impact by augmenting the effective services provided by materials. That is, higher quality materials may provide more material services, which contribute more to production. In Online Appendix B, we consider an alternative model that accounts for the input-output quality linkage and the effective material services impact. We show that the alternative model is equivalent to our model for the purpose of this study. In particular, the two models generate the same estimates of the quality-adjusted material prices and productivity, which are our focus.

[11] This paper focuses on material quality as in Kugler and Verhoogen (2012) rather than the quality of capital and labor for three reasons. First, the material expenditure share in total variable cost is much larger (around 85% on average) than the shares of labor and capital; thus, material quality potentially has a much larger impact on output quality and productivity. Second, given that we are interested in comparing material prices as a proxy for procurement corruption, it is of particular importance to tease out material quality in the price measure. Third, it is unlikely that the potential differences in labor and capital quality will drive our empirical results. This is because the within-industry labor quality difference is low in our sample. For example, the 2004 Chinese Census data show that 97.7% of workers had no college degree and over 82% of the firms employed zero college-educated labor in 15 of the 19 industries under consideration. The share of college-educated employees was also small for the firms that hired college-educated workers, given the small share of college-educated workers in the total workforce. We use the deflated book value of capital as a proxy for capital services following the tradition in the literature, which potentially accounts for the capital quality differences.

where ϵ_{jt+1}^{ω} is an i.i.d. shock to firm productivity. SOE_{jt} is a dummy indicating whether the firm is an SOE or not, and similarly $SASAC_t$ is a dummy indicating the SASAC is established or not. By including these two dummies in the evolution processes, in the spirit of Chen et al. (2017), we allow for different steady states for SOEs and non-SOEs as well as before and after SASAC.[12]

The variation in the unit price of physical material inputs across firms reflects two sources of heterogeneity: vertically differentiated input quality due to the firm's choice of H_{jt}, and a quality-adjusted materials price faced by the firm (denoted P_{Mjt}). As a result, even if firms were using the same quality of materials, the unit prices they would face may still differ. We capture this feature in a simple form:[13]

$$\tilde{P}_{Mjt} = P_{Mjt} H_{jt}. \tag{5}$$

We call $\tilde{P}_{Mjt}$ the quality-inclusive unit prices.[14] We denote $p_{Mjt} = \ln P_{Mjt}$ and assume that it evolves according to an AR(1) process:

$$p_{Mjt+1} = g_0 + g_{soe} SOE_{jt} + g_{SASAC} SASAC_t + g_1 p_{Mjt} + \epsilon_{jt+1}^{p}, \tag{6}$$

where ϵ_{jt+1}^{p} is an i.i.d. shock to input prices. This specification allows for different steady states of input prices for SOEs and non-SOEs, which also differ before and after SASAC.

We allow P_{Mjt} to differ across firms for a wide range of possibilities, such as firm characteristics (i.e., size, location, and ownership), non-optimality, frictions, and distortions. In particular, as the focus of the paper, SOEs, on the one hand, may have privileges over non-SOEs (and thus face lower input prices) because of SOEs' greater bargaining power, connections to the local/central government, and/or access to other SOEs in upstream industries. On the other hand, ineffective external monitoring of SOE management may increase shirking or even corruption in input procurement, which may increase the input prices SOEs pay. Our methodology for recovering P_{Mjt} does not impose a priori assumptions on whether SOEs face lower or higher quality-adjusted input prices (P_{Mjt}) compared with non-SOEs. In addition, even if SOEs' quality-adjusted prices are higher than those faced by non-SOEs, it is not

[12]We tested different specifications of the Markov processes of productivity and input prices and found that the results on the impact of external monitoring are very robust. These specifications include (1) restrictive evolution processes that are shared by both types of firms before and after SASAC; (2) flexible evolution processes that control for oversight distance and its interactions with SASAC and SOE dummies; and (3) nonparametric Markov processes, as approximated by a full set of polynomials up to the third order with respect to productivity, SASAC dummy, SOE dummy, and oversight distance. The results from the latter two specifications are reported in Tables OA20 and OA21 in the Online Appendix.

[13]Grieco et al. (2019) consider a more general form, $\tilde{P}_{Mjt} = P_{Mjt} H_{jt}^{\phi}$, where the parameter ϕ captures the price effect of input quality and is flexibly estimated. The estimation results show that ϕ is very close to one using the same data. So in this paper, we fix the price to be linear in H_{jt} for simplicity.

[14]$\tilde{P}_{Mjt}$ does not rely on the quantity purchased, M_{jt}. This implies that the material expenditure, E_{Mjt}, is the product of the unit price ($\tilde{P}_{Mjt}$) and the quantity purchased (M_{jt}). However, this does not exclude the possibility that larger firms face lower unit prices ($\tilde{P}_{Mjt}$). For example, a larger firm with bargaining power (say, bulk purchases) may face lower quality-adjusted prices (P_{Mjt}) than of a smaller firm, so if they chose the same quality of input, then the unit price of the larger firm would be lower.

necessarily true that SOEs' quality-inclusive prices ($\tilde{P}_{Mjt}$) are higher. For example, if SOEs tend to have lower productivity, they may find it optimal to choose lower quality inputs and hence, $\tilde{P}_{Mjt}$, the quality-inclusive unit input prices may be lower for SOEs compared with non-SOEs. For this reason, it is the quality-adjusted price P_{Mjt} that serves as a key measure of firms' ability to secure better material prices in the comparison between SOEs and non-SOEs.

Observing its capital stock, productivity, quality-adjusted input prices, and wage rate (P_{Ljt}), each firm maximizes its profit by choosing labor and material quantity, material quality, and output:

$$\begin{aligned}\pi(P_{Mjt}, \omega_{jt}, K_{jt}, P_{Ljt}) = \max_{L_{jt}, M_{jt}, \tilde{Q}_{jt}, H_{jt}} \quad & P_{jt}\tilde{Q}_{jt} - \tilde{P}_{Mjt}M_{jt} - P_{L_{jt}}L_{jt}, \\ \text{subject to:} \quad & (1),\ (2) \text{ and } (5).\end{aligned} \tag{7}$$

3.2.2 Estimation Method

We estimate the model to recover the quality-adjusted material prices (p_{Mjt}) and productivity (ω_{jt}) with a two-step procedure. The method takes advantage of the structural model of production decisions and estimates the production function using commonly observed variables including labor employment, wage expenditure, material expenditure, capital stock, and revenues. In the first step, we use firms' optimization conditions on labor and material quantity choices together with data on wages and material expenditures to infer quality-inclusive input prices and productivity. In the second step, we further use the condition associated with firms' optimal material quality choice to purge the quality from the recovered quality-inclusive input prices and productivity.

Specifically, the firm's profit maximization problem defined in (7) implies the following first-order conditions (FOCs) for output quantity, labor quantity, and material quantity:

$$\frac{\partial \mathcal{L}}{\partial \tilde{Q}_{jt}} = \frac{1+\eta}{\eta}(\tilde{Q}_{jt})^{1/\eta} - \mu_{jt} = 0, \tag{8}$$

$$\frac{\partial \mathcal{L}}{\partial L_{jt}} = -P_{L_{jt}} + \mu_{jt}\tilde{\Omega}_{jt}\frac{\partial F}{\partial L_{jt}} = 0, \tag{9}$$

$$\frac{\partial \mathcal{L}}{\partial M_{jt}} = -\tilde{P}_{M_{jt}} + \mu_{jt}\tilde{\Omega}_{jt}\frac{\partial F}{\partial M_{jt}} = 0, \tag{10}$$

where P_{jt} is replaced by demand and μ_{jt} is the Lagrange multiplier of the production constraint.

Taking the ratio of (9) and (10), we can solve the unobserved material quantity M_{jt} as a function of observed variables up to a set of parameters to be estimated:

$$M_{jt} = \left[\frac{\alpha_L E_{Mjt}}{\alpha_M E_{Ljt}}\right]^{\frac{1}{\gamma}} L_{jt}, \tag{11}$$

where $E_{Ljt} = P_{Ljt}L_{jt}$ and $E_{Mjt} = \tilde{P}_{Mjt}M_{jt}$. Because $E_{Mjt} = \tilde{P}_{Mjt}M_{jt}$, we have:

$$\tilde{P}_{Mjt} = \left[\frac{\alpha_M}{\alpha_L}\right]^{\frac{1}{\gamma}} \left[\frac{E_{Mjt}}{E_{Ljt}}\right]^{1-\frac{1}{\gamma}} P_{Ljt}. \tag{12}$$

Next, we can write $\tilde{\Omega}_{jt}$ as a function of observed variables, by substituting (8) into the FOC for labor (9) and replacing $\tilde{Q}_{jt}$ by the production function and M_{jt} by (11):

$$\tilde{\Omega}_{jt} = \frac{1}{\alpha_L}\frac{\eta}{1+\eta}L_{jt}^{-\gamma}E_{L_{jt}}\left[\alpha_L L_{jt}^{\gamma}\left(1+\frac{E_{M_{jt}}}{E_{L_{jt}}}\right)+\alpha_K K_{jt}^{\gamma}\right]^{1-\frac{1}{\gamma}(1+\frac{1}{\eta})}. \tag{13}$$

In addition, we recover $\tilde{Q}_{jt}$ by substituting (11) and (13) back into the production function (2).

Therefore, we recover $(M_{jt}, \tilde{P}_{M_{jt}}, \tilde{Q}_{jt}, \tilde{\Omega}_{jt})$ uniquely from observable data $(E_{Ljt}, E_{Mjt}, L_{jt}, K_{jt}, R_{jt})$ up to a set of parameters to be estimated. The estimation equation is constructed by plugging all these recovered variables into the revenue function $R_{jt} = P_{jt}\tilde{Q}_{jt}e^{u_{jt}}$:

$$R_{jt} = \frac{\eta}{1+\eta}\left[E_{M_{jt}} + E_{L_{jt}}\left(1+\frac{\alpha_K}{\alpha_L}\left(\frac{K_{jt}}{L_{jt}}\right)^{\gamma}\right)\right]e^{u_{jt}}, \tag{14}$$

where u_{jt} is a measurement error with an independent and identical distribution.

The model parameters $\beta \equiv (\alpha_L, \alpha_M, \alpha_K, \eta, \gamma)$ can be identified and estimated by a nonlinear least squares estimator implied by (14) with two additional constraints naturally implied by the model:

$$\begin{aligned}\hat{\beta} \quad &= \quad \text{argmin}_{\beta}\sum_{jt}\left[\ln R_{jt} - \ln\frac{\eta}{1+\eta} - \ln\left\{E_{M_{jt}} + E_{L_{jt}}\left(1+\frac{\alpha_K}{\alpha_L}\left(\frac{K_{jt}}{L_{jt}}\right)^{\gamma}\right)\right\}\right]^2 \\ &\quad\ \text{subject to:} \qquad \alpha_L + \alpha_M + \alpha_K = 1, \qquad \frac{\alpha_M}{\alpha_L} = \frac{\overline{E}_M}{\overline{E}_L}.\end{aligned} \tag{15}$$

The first constraint is a normalization of share parameters in the CES production function. The second constraint equalizes the ratio of geometric means of labor expenditure ($\overline{E}_L$) and material expenditure ($\overline{E}_M$) to the ratio of share parameters in the CES production function. It results directly from taking the geometric means of the FOCs for labor and material quantities of all firms.

With β estimated, we can recover $\tilde{\Omega}_{jt}$ and $\tilde{P}_{Mjt}$ from (12) and (13), respectively. However, they both contain input quality H_{jt}. $\tilde{\Omega}_{jt}$ contains input quality because it echoes the linkage between input quality and output quality; $\tilde{P}_{Mjt}$, by definition, is $P_{Mjt}H_{jt}$, thus it also contains input quality. To recover the quality-adjusted input price p_{Mjt} and productivity ω_{jt}, we use the firm's optimization condition for input quality choice. Specifically, the FOC of endogenous input quality choice is

$$\frac{\partial\tilde{P}_{Mjt}(P_{Mjt}, H_{jt})}{\partial H_{jt}}M_{jt} = \mu_{jt}F(L_{jt}, M_{jt}, K_{jt})\frac{\partial\tilde{\Omega}_{jt}}{\partial H_{jt}}. \tag{16}$$

Solving μ_{jt} from (10), plugging it into (16), and after some algebra we derive a closed-form relationship between the endogenous input quality and productivity:

$$h_{jt} \quad = \quad \frac{1}{\theta} \ln \frac{\sigma_{Mjt}}{1 - \sigma_{Mjt}} + \omega_{jt}, \tag{17}$$

where $h_{jt} = \ln(H_{jt})$ is the input quality in logarithm and $\sigma_{Mjt} = (\partial F / \partial M_{jt}) \cdot (M_{jt}/F(\cdot))$ is the output elasticity of material. σ_{Mjt} can be directly computed according to the estimated production parameters and material input quantity after estimating (15).

Substituting (17) into (3) to solve for productivity (ω_{jt}), and using the price menu function (5) to solve for quality-adjusted prices (p_{Mjt}), we obtain:

$$\omega_{jt} \quad = \quad \ln \tilde{\Omega}_{jt} - \frac{1}{\theta} \ln \left[\frac{1}{1 - \sigma_{Mjt}} \right], \tag{18}$$

$$p_{Mjt} \quad = \quad \ln \tilde{P}_{Mjt} - \ln \tilde{\Omega}_{jt} - \frac{1}{\theta} \ln(\sigma_{Mjt}). \tag{19}$$

That is, ω_{jt} and p_{Mjt} can be written as functions of estimated variables up to the quality-productivity complementarity parameter θ. We estimate θ together with the Markov process parameters in (4) and (6) via the generalized method of moments with moment conditions:

$$\hat{\vartheta} \quad = \quad \operatorname{argmin}_{\vartheta} \left[\sum_{jt} \mathbf{Z_{jt}} \otimes (\epsilon^{\omega}_{jt+1}, \epsilon^{p}_{jt+1}) \right]' \mathbf{W} \left[\sum_{jt} \mathbf{Z_{jt}} \otimes (\epsilon^{\omega}_{jt+1}, \epsilon^{p}_{jt+1}) \right], \tag{20}$$

where $\vartheta \equiv (\theta, f_0, f_1, f_{soe}, f_{SASAC}, g_0, g_1, g_{soe}, g_{SASAC})$, $\epsilon^{\omega}_{jt+1} = \omega_{jt+1} - f_0 - f_1\omega_{jt} - f_{soe}SOE_{jt} - f_{SASAC}SASAC_t$, and $\epsilon^{p}_{jt+1} = p_{Mjt} - g_0 - g_1 p_{Mjt-1} - g_{soe}SOE_{jt} - g_{SASAC}SASAC_t$. $\mathbf{W}$ is a weighting matrix. The set of instrumental variables, $\mathbf{Z_{jt}}$, includes $\ln K_{jt}$, $\ln E_{Mjt}$, $\ln E_{Ljt}$, $\ln L_{jt}$, $\ln K_{jt} \ln E_{Mjt}$, and $\sigma_{M_{jt}}$. With ϑ estimated, we compute the quality-adjusted productivity and input price measures from (18) and (19), respectively.

In addition to the two key measures, we also estimate a measure of TFP following Levinsohn and Petrin (2003) to contrast our study with the traditional analysis of SOEs' productivity. We follow the common practice of using material expenditure deflated by a price index as a proxy for material quantity. As discussed in Grieco et al. (2016), this productivity measure may be biased in the presence of input price heterogeneity, and it is silent on the heterogeneity of input prices across firms and over time. We use it as a safeguard to show that our preferred productivity measure ω_{jt} indeed captures the key productivity concept that has been studied in the literature.

Discussion. The estimation methodology requires the *production unit* of each firm to choose labor and material quantity to maximize profit, given productivity, input prices, and capital. Similar assumptions are commonly employed in a broad set of applications in related literature.[15] Moreover, it is critical to note that this methodology allows for many other types of non-optimal decisions as well as various types of distortion and resource misallocation across firms. First, it allows for distorted input prices faced by individual firms caused by managers' corruption and self-dealing in the procurement process, as shown in the theoretical analysis, as well as other forms of market friction or market power (e.g., geographic location, transportation costs, and firm size). For example, firms in remote areas may pay higher input prices due to transportation costs or localized input markets; larger firms may be more capable of negotiating for lower input prices. Second, the methodology also allows for productivity heterogeneity driven by many factors, including difference in external monitoring strength. Finally, this methodology accommodates many types of distortion and misallocation among firms. For example, supported by government, SOEs usually have priority in access to more advanced equipment and technology, which potentially increases their productivity. Meanwhile, SOEs might also invest more in capital compared with non-SOEs, because SOEs have better/cheaper access to financial resources (e.g., Berkowitz et al., 2017), which results capital misallocation among firms. Allowing for these features is especially important for this study, to ensure that our key result is not driven by different distortions and misallocation between SOEs and non-SOEs.

3.3 Estimation Results

We estimate the model industry by industry. The full results are reported in Online Appendix Tables OA5 and OA6, in which the top panels report the parameters in the production and demand functions and the bottom panels report the the parameters in (3) and the Markov processes of productivity and input prices. The output elasticity of material inputs, $\hat{\alpha}_M$, is significantly larger than $\hat{\alpha}_L$ and $\hat{\alpha}_K$. This is consistent with the common observation of large material expenditure shares in production in Chinese industries. We find that the elasticity of substitution among capital, labor, and material is significantly greater than one, ranging from 1.2 to 2.7 among all industries. This finding is somewhat surprising, because the elasticity estimate is usually less than one when using data from developed countries without controlling for the heterogeneity of input prices. However, this result corroborates the findings of Berkowitz et al. (2017), who estimate an average elasticity of substitution among industries at 1.4 using the same data but a different estimation method. It is also consistent with the findings of Grieco et al. (2016), who use the same method but different data from a Colombian plant-level survey of a variety of industries.

[15] See, for example, Katayama et al. (2009); Epple et al. (2010); Gandhi et al. (2020); De Loecker (2011); De Loecker and Warzynski (2012); Zhang (2019); Doraszelski and Jaumandreu (2013). Online Appendix D provides further evidence to show that this assumption is reasonable in the context of China during the sample period. Online Appendix E discusses the potential impact of different labor frictions between SOEs and non-SOEs, if any, and shows that our results are robust.

We also find that the elasticities of substitution (i.e., $\frac{1}{1-\theta}$) between productivity and input quality are well below one: they range from 0.167 in the agricultural products industry, to 0.567 in the rubber industry. The results imply that productivity and input quality are complements. Therefore, firms with higher productivity will endogenously choose to use inputs of higher quality. Given that the unit input price is increasing in quality, the complementarity suggests that firms with higher productivity are associated with higher unit input prices. This corroborates the finding of positive correlation between firm productivity and input prices in Kugler and Verhoogen (2012), and it is also consistent with the estimate in Grieco et al. (2019) using a four-digit SIC Chinese industry.

The estimation results show that productivity and input prices evolve differently for SOEs and non-SOEs, and the evolution differs before and after SASAC. This finding is captured by the significant coefficients on the SOE and SASAC dummies in both evolution equations. The persistence parameters for productivity range from 0.555 to 0.961 across industries, which is within the order of persistence documented in the literature, such as Foster et al. (2008). The persistence parameters of input prices are well above 0.9 across industries. They are close to the estimate of Grieco et al. (2019) using the same methodology, but higher than that found in Atalay (2014) where firm-level input prices and quantities are observed. This difference may be due to the input price measures in Atalay (2014) containing input quality, which is likely to be more volatile because it is an endogenous firm choice. In contrast, our price measure p_{Mjt} is quality-adjusted and its variation captures firm characteristics (other than input quality) such as geographic location, firm size, and ownership status, which are usually very persistent.

The distributions of productivity and quality-adjusted prices also present reasonable properties. The inter-quantile range of productivity ω is between 0.716 and 1.134 across industries. It is close to the results in Hsieh and Klenow (2009) using data from China and India, as well as Syverson (2004) using four-digit SIC industries in U.S. manufacturing sectors. The dispersion of the quality-adjusted input prices, p_{Mjt}, is much smaller. The inter-quantile range is between 0.159 and 0.374. However, the dispersion is still large economically. For example, an inter-quantile range of 0.159 implies that the input price (given the level of input quality) paid by the 75th percentile firm in the distribution is about 17.2% ($e^{0.159} - 1 \approx 0.172$) higher than that paid by the 25th percentile firm.

4 Effect of External Monitoring

The central question of this paper is how does external monitoring of firm management by the government affect the performance of SOEs? We use three performance measures to answer this question: traditional TFP and our preferred measures of input prices and productivity. The traditional revenue-based TFP is estimated following Levinsohn and Petrin (2003), and it generically measures the profitability of firms echoing Figure 1. The separate accounts of input prices and productivity from our preferred method provide evidence on the channels through which external monitoring can have an impact. To proceed, we first compare the performance of SOEs and non-SOEs in terms of productivity and input prices. Then, we test the causal relationship between external monitoring and SOE performance, using the variation in monitoring strength in the time and spatial dimensions.

4.1 SOEs versus Non-SOEs

As discussed in Section 2, Chinese SOEs faced ineffective external monitoring of their management compared with non-SOEs. As a result, we predict that SOEs face higher material input prices and have lower productivity compared with their non-SOE counterparts, other things being equal, as shown in the stylized model in Online Appendix C. To test this conjecture, we estimate the following equation:

$$Y_{jt} = \beta_0 + \beta_{soe} SOE_{jt} + \beta_z Z_{jt} + \lambda_{ind} + \lambda_{prov} + \lambda_t + \varepsilon_{jt}, \tag{21}$$

where Y_{jt} is the outcome variable for firm j in year t. We consider three outcome variables. The first two are input prices (p_{Mjt}) and productivity (ω_{jt}) recovered from our preferred approach, which explicitly separates input price heterogeneity from productivity. The third outcome variable, as a safeguard for comparison, is the traditional TFP measure estimated following the method of Levinsohn and Petrin (2003) using deflated material expenditure as a proxy for material quantity. The parameter of interest is β_{soe}, which is the coefficient on the dummy variable SOE_{jt}. SOE_{jt} equals 1 if and only if the firm has state ownership greater than 30%. So β_{soe} measures the difference in the outcome variables between SOEs and non-SOEs. Z_{jt} contains a series of firm characteristics, such as firm age and size (capital stock). It also contains measures of firm technology characteristics, including a lagged research and development (R&D) investment dummy and capital intensity. In addition, we control for industry fixed effects (λ_{ind}), province fixed effects (λ_{prov}), and time fixed effects (λ_t) to capture cross-section differences and common time trends. The error term ε_{jt} is an i.i.d. shock.

The estimation results confirm the conjecture. SOEs pay input prices that are 6.4% higher on average compared with their non-SOE counterparts after controlling for observable differences such as size, industry, and location, as reported in the full-fledged specification in column (2) in Table 2. Because material inputs account for over 80% of the total variable cost, the impact of such input price difference is quite significant—it translates to a difference of about 5.1% in the profit rate. At the same time, SOEs' productivity is substantially lower than that of non-SOEs on average: as reflected in column (4), the productivity gap between the two groups is 19.9%.

Two opposite forces drive the results. On the one hand, SOEs' stronger bargaining power, access to

Table 2: *Performance Comparison of SOEs and Private Firms*

	(1) Input price	(2) Input price	(3) Productivity	(4) Productivity	(5) TFP	(6) TFP
SOE	0.067***	0.064***	-0.226***	-0.199***	-0.170***	-0.161***
	(0.001)	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity		YES		YES		YES
Observations	1,196,053	873,414	1,196,053	873,414	1,196,053	873,414
Adjusted R^2	0.943	0.967	0.928	0.966	0.685	0.725

Standard errors (clustered at the firm level) are in parentheses.

Added constant and fixed effects of province, year, industry, and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

discounted material prices due to their large size, and connections to the government/upsteam SOEs may enable them to access lower input prices. Advanced technologies and newer capital vintage may also improve the productivity of SOEs. However, on the other hand, with weak external monitoring, SOE managers may shirk in negotiating better prices, take kickbacks, and be involved in relational transactions and self-dealing, all of which may drive up the input prices SOEs pay. And shirking in production management may impair production efficiency and lead to low productivity. The results show that the latter force dominates.

Using the traditional TFP as the measure of firm performance, as a comparison, we find qualitatively similar results: SOEs on average underperform non-SOEs. In column (6) in Table 2, SOEs' TFP is about 16.1% lower than that of non-SOEs, which corroborates the literature that documents the productivity gap between the two groups (e.g., Jefferson and Rawski, 1994; Xu, 2011; Brandt et al., 2012; Hsieh and Song, 2015). This finding is also consistent with the results based on our preferred measure of productivity. The difference in TFP implies that our preferred productivity measure ω_{jt} indeed captures the key efficiency concept that has been studied in the literature. More importantly, the results using ω_{jt} as the performance measure reflect that the productivity gap still exists even after the input price heterogeneity is controlled.

Nonetheless, the above results do not necessarily imply causality, because other factors aside from external monitoring (e.g., differences in labor hiring/firing frictions between SOEs and non-SOEs) might also contribute to the price difference. To explore the causality, in the remainder of this section, we examine how the changing intensity of external monitoring due to the establishment of SASAC and differential monitoring costs can affect SOE performance.

4.2 SASAC and SOE Performance: Time Dimension Evidence

This subsection investigates the impact of the establishment of SASAC as a nationwide quasi-experimental policy shock on SOE performance. Because SASAC strengthened the external monitoring of SOEs but not non-SOEs, the differential responses of these two types of firms after SASAC help us identify the impact of monitoring from the time dimension.

4.2.1 Graphic Preview

We present the distribution of input prices, productivity, and TFP to visualize the potential impact of SASAC on firm performance, without controlling for other firm characteristics. Because our estimation approach implicitly assumes different normalization points for productivity and input price measures for each industry,[16] *direct* cross-sectional comparison between industries is invalid without controlling for industry fixed effects.[17] Thus, we focus on contrasting the *changes* in the distributions before and after the establishment of SASAC, separately for SOEs and non-SOEs.

In Figure 2, we contrast the distribution of input prices (p_{Mjt}) before and after SASAC, separately for SOEs and non-SOEs. While the input price distribution remains almost unchanged for non-SOEs before and after SASAC, we observe a large drop for SOEs after SASAC. This is consistent with the conjecture that the strengthened external monitoring of SOEs from SASAC (but not of non-SOEs) may have reduced shirking in bargaining for better input prices and/or managerial expropriation in material procurement among SOEs only. Figure 3 shows that productivity improved substantially for both SOEs and non-SOEs after SASAC. The improvement may have been caused by multiple reasons, such as a growing trend of technology and implementation of policies (e.g., SASAC). However, the growth for SOEs is larger than that for non-SOEs. When using TFP as a performance measure, as shown in Figure 4, we observe a similar pattern: the distribution of TFP shifted to the right substantially after SASAC for SOEs, but only slightly for non-SOEs. Overall, the evidence suggests that SASAC may have an impact on SOE performance.

Of course, entry/exit, privatization of SOEs, and different growth trends of SOEs and non-SOEs

[16] We normalize the inputs (labor, material, and capital) of the CES production function using their industry-level geometric means following the literature (e.g., Klump and de La Grandville, 2000; León-Ledesma et al., 2010). So the different normalization points enter the recovered productivity and input prices additively (in logarithm), by changing their location (but not dispersion). For this reason (and to take away the industry difference), we normalize the input prices, productivity, and TFP measures of individual firms by their corresponding industry means in Figure 2, 3, and 4.

[17] For example, consider an extreme case where industry 1 consists of SOEs only and industry 2 consists of non-SOEs only. Suppose the actual productivity distributions of the two groups are identical, but the mean productivity in industry 1 is normalized to be zero while the mean productivity in industry 2 is normalized to be one. This directly implies that the productivity of non-SOEs is higher than that of SOEs, although the truth is that they are identical. However, the comparison over time is feasible because the normalization is the same over time.

Figure 2: *Distributions of p_M before and after SASAC, by Group*

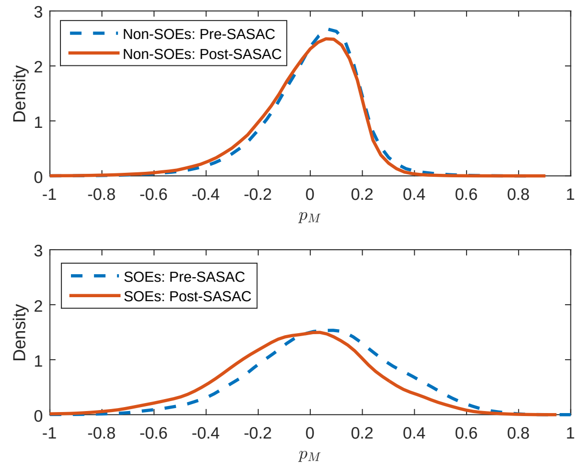


Figure 3: *Distributions of ω before and after SASAC, by Group*

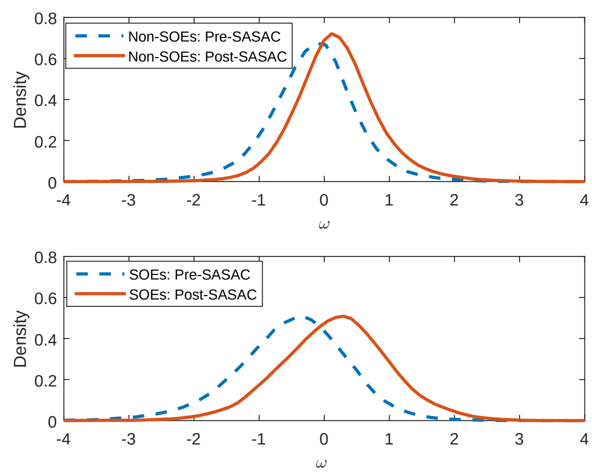


Figure 4: *Distributions of TFP before and after SASAC, by Group*

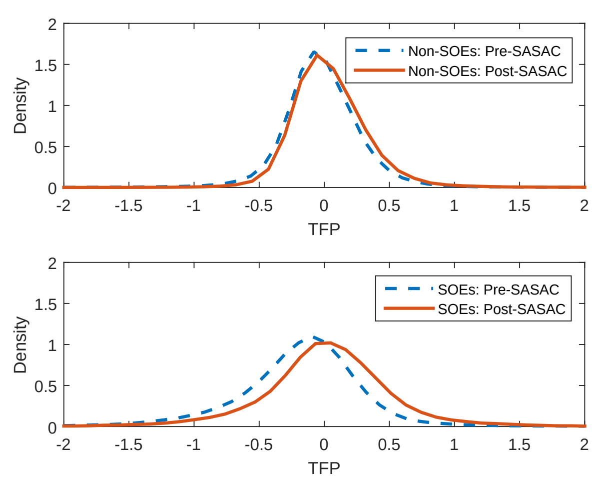
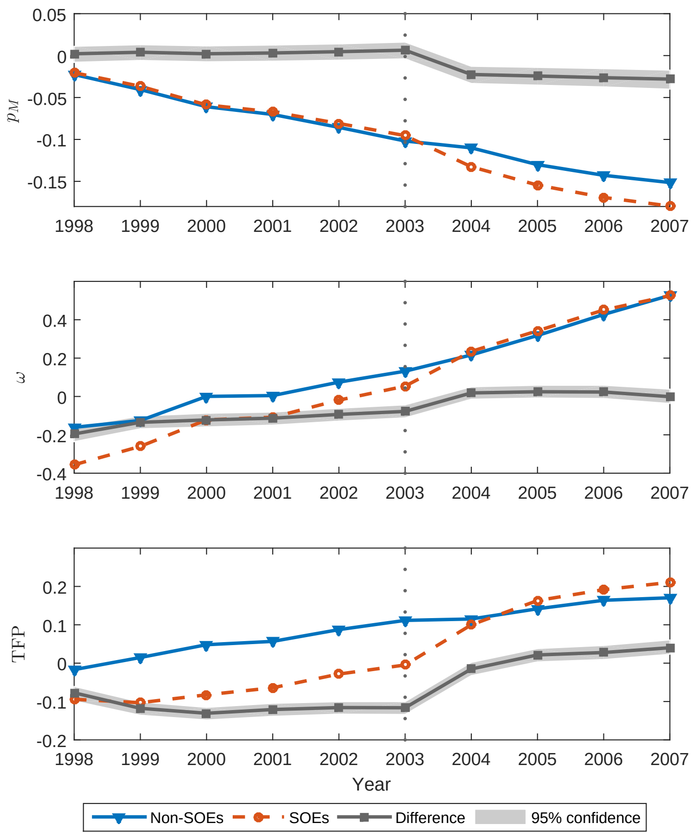


Figure 5: *Evolution of the Means of the Key Measures, by Group*



may also contribute to these patterns. To show that the patterns are robust to these alternative potential drivers, we zoom in our comparison on a balanced sample after dropping entrants, exiters, and privatized SOEs during the data period. The results are reported in Figure 5. We present the evolution of average input prices, productivity, and TFP over the data period for SOEs and non-SOEs separately, as well as their differences.[18] Although the performance of SOEs was relatively weaker before 2003 in all three measures, the gaps relative to non-SOEs narrowed immediately after the establishment of SASAC and afterward remained at a similar level. From 2003 to 2004, the gap reduced by 2.9, 9.6, and 10.1 percentage points, respectively, for input prices, productivity, and TFP.[19] More interestingly, the closing of the gaps was almost entirely due to the catch-up of SOEs, rather than the down-performing of non-SOEs. Indeed, non-SOEs grew steadily over the data period. This finding is consistent with the observation of the closing of the profit gap between SOEs and non-SOEs in *The China Statistical Yearbook 2007*. In addition, the two types of firms share almost the same trend for all three key measures before SASAC, especially for input prices and TFP. This finding validates our use of difference-in-differences analysis in the empirical results.[20]

[18] The documented patterns are robust when we use medians or levels (rather than logarithm) of the key measures.

[19] Although the balanced panel shows that SOEs outperformed non-SOEs after 2004 in all three key measures on average, this is not the case for the unbalanced panel in general.

[20] Online Appendix G.6 shows that the results are robust even after explicitly dealing with potential pre-trends.

In general, these patterns are consistent with the conjecture that the establishment of SASAC, as a mechanism to strengthen external monitoring of SOEs exclusively, may have contributed substantially to the performance of SOEs, as predicted by the stylized model in Online Appendix C.

4.2.2 Baseline Estimation Results

For a formal investigation of the impact of the strengthened monitoring after SASAC, as summarized by the above conjecture, we estimate the following equation:

$$Y_{jt} = \beta_0 + \beta_{soe} SOE_{jt} + \beta_{soe*SASAC} \left(SOE_{jt} * SASAC_t \right) + \beta_z Z_{jt} + \lambda_{ind} + \lambda_{prov} + \lambda_t + \varepsilon_{jt}. \tag{22}$$

Because the central government-level SASAC was established in March 2003, and the province-level SASACs for all 31 provinces were established during the period afterward until early 2004, we define the cutoff year for dummy $SASAC_t$ as 2004. That is, $SASAC_t$ equals 1 from 2004 onward.[21] All other variables in this equation are similarly defined as in (21). Since time dummies are included, the key parameter of interest, $\beta_{soe*SASAC}$, measures the impact of SASAC on SOEs, relative to non-SOEs. In Online Appendix G, we examine a broad set of specifications as robustness checks, by considering privatization, market competition, SOE privilege enhancement, entry/exit, alternative definitions of SOEs, firm fixed effects, and international trade participation.

As the baseline specification, we first examine the impact of SASAC on SOEs via the input price and productivity channels using our preferred measures. As reported in Table 3, SASAC reduces the input prices paid by SOEs substantially, relative to non-SOEs. In our preferred regression in column (2), we find that SASAC lowers the input prices of SOEs by 3.9% on average relative to non-SOEs. As SOEs paid 7.6% higher input prices than non-SOEs before SASAC, as captured by the coefficient on SOE_{jt} in column (2) in this table, such a reduction in SOEs' input prices indeed closes the gap between the two groups by half. This reduction reflects the impact arising from the strengthened external monitoring of SOEs after SASAC, which put more pressure on SOE managers to bargain harder for better input prices and reduced corruption in input procurement. This result corroborates the findings in Becker and Stigler (1974), which suggest that the right combination of monitoring and punishment can reduce corruption. Considering the heavy expenditure on material inputs, SASAC's impact on input prices is very meaningful for the rate of profit. The 3.9% reduction in input prices roughly contributes to an increase in the profit rate by about 3.1 percentage points.

We also find that SASAC has a significant and positive impact on our measure of productivity, as

[21] We also conduct a robustness check in Online Appendix G to show that our results are robust using a subsample after dropping all observations in the transition year 2003.

Table 3: *SASAC and SOE Performance*

	(1) Input price	(2) Input price	(3) Productivity	(4) Productivity	(5) TFP	(6) TFP
SOE	0.082***	0.076***	-0.283***	-0.239***	-0.200***	-0.191***
	(0.001)	(0.001)	(0.005)	(0.003)	(0.002)	(0.003)
SASAC*SOE	-0.056***	-0.039***	0.213***	0.126***	0.113***	0.095***
	(0.001)	(0.001)	(0.006)	(0.004)	(0.004)	(0.004)
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity		YES		YES		YES
Observations	1,196,053	873,414	1,196,053	873,414	1,196,053	873,414
Adjusted R^2	0.943	0.967	0.929	0.966	0.686	0.726

Standard errors (clustered at the firm level) are in parentheses.

Constant and fixed effects of province, year, industry, and registration affiliation are included in all the regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

reported in columns (3) and (4) in Table 3 after controlling for various firm characteristics. In the full-fledged regression in column (4), SASAC increases the productivity of SOEs by 12.6% relative to non-SOEs. Compared with the pre-SASAC productivity difference (23.9%) between SOEs and non-SOEs, this impact is large—it reduces the productivity gap by over half. This result provides evidence that SASAC may have substantially reduced shirking in production management through its strengthened monitoring, which drives up the productivity of SOEs.

When using the traditional TFP, we find similar results—SASAC improves the TFP of SOEs relative to non-SOEs. In the full-fledged specification reported in column (6) in Table 3, SASAC increases SOEs' TFP by 9.5% on average, relative to non-SOEs. The gap between SOEs and non-SOEs before SASAC, is 19.1%. This suggests that SASAC reduces the TFP gap between SOEs and non-SOEs by about half.

These results are robust after controlling for various firm characteristics, as well as in the robustness checks in Online Appendix G.[22] In sum, the results show that the strengthened external monitoring of management due to the establishment of SASAC in 2003, as a quasi-experiment in the time dimension that only affects SOEs, substantially reduced the gaps in input prices and productivity between the two groups of firms. Admittedly, this analysis does not account for the possibility that SASAC might also have an indirect effect through input-output linkages. For example, if SOEs in an upstream industry have improved productivity or lower input prices due to strengthened monitoring, then their downstream firms can also benefit from it if there is price pass-through. Because this benefit from the input-output linkage happens at the industry level by influencing not only SOEs but also non-SOEs,

[22] We also examine the differential performance of SOEs supervised by different tiers of governments in Table OA12. We find that central and province-level SOEs, which are typically larger and face stronger external monitoring than city-level SOEs, performed better in input prices and productivity. SASAC has a larger effect on city-level SOEs, presumably due to their larger potential gains, and, as a result, SASAC might have implemented a higher order of monitoring on them. This result is robust after controlling for market share as a proxy for market power.

the overall effect of SASAC would be larger than our estimate if the indirect effect is considered.

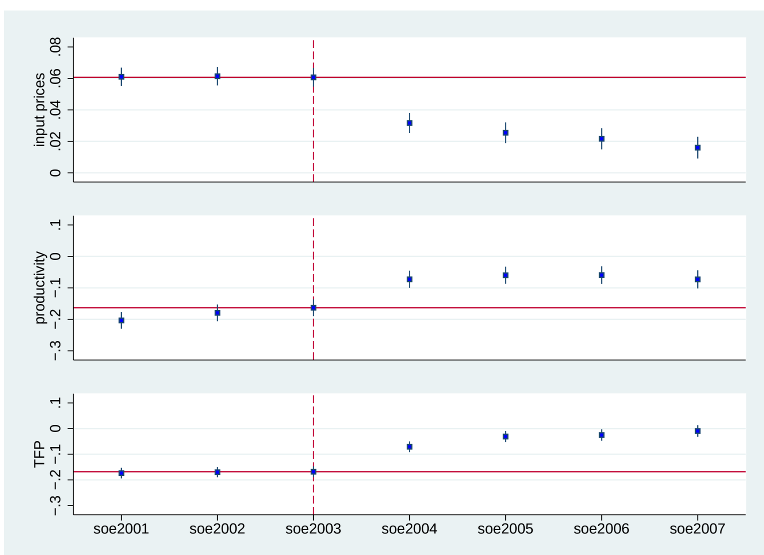
4.2.3 Dynamic Effects and Pre-Trend

This subsection serves two purposes. First, we test the dynamic effect of SASAC. Second, we test the common-trend assumption between SOEs and non-SOEs before SASAC, which is the basis for our difference-in-differences style analysis. For these purposes, we extend (22) in two ways. First, we incorporate a full set of interactions between the SOE and time dummies after 2004 to capture the dynamic effect of SASAC. Second, we add the interaction between the SOE dummy and year dummies for one year, two years, and three years before SASAC to test for any differential pre-trends between these two groups of firms before SASAC. Specifically, we estimate the following equation:

$$Y_{jt} = \beta_0 + \beta_{soe} SOE_{jt} + \sum_{t=2001}^{2007} \beta_{soe*t} \left(SOE_{jt} * D_t\right) + \beta_z Z_{jt} + \lambda_{ind} + \lambda_{prov} + \lambda_t + \varepsilon_{jt}, \tag{23}$$

where D_t is the time dummy, and β_{soe*t} measures the differential performance of SOEs relative to non-SOEs in year t. To ensure that the results are not driven by entry and exit, we estimate (23) based on the aforementioned balanced panel. The estimation results for β_{soe*t} are visualized in Figure 6, with point estimates and 95% confidence intervals.

Figure 6: *Dynamic Effect of SASAC and Test for Pre-trend:* β_{soe*t}



Note: The range represents the 95% confidence interval of the parameter estimates.

Three interesting observations stand out. First, there is a sharp change in β_{soe*t} from 2003 to 2004 even in this flexible specification, lending further evidence of the differential impact of SASAC on SOEs compared with non-SOEs. In particular, SOE input prices dropped and productivity jumped significantly after 2003, relative to non-SOEs. The TFP estimates show a similar pattern. These results are consistent with the conjecture that SASAC enhanced external monitoring strength, which effectively reduced material procurement corruption and shirking in production management.

Second, there is an obvious dynamic effect of SASAC on input prices, but not on productivity. After the large drop in 2004, the estimates of β_{soe*t} in the input price regression continue to drop further (at a rate that is faster than that, if any, before SASAC). For productivity, β_{soe*t} almost remains stable after the large jump in 2004. The impact of SASAC on TFP, which in principle contains the impacts on input prices and productivity, shows a similar pattern as that for input prices.

The final observation is that there is no obvious pre-trend for input prices and TFP. As shown in the figure, from 2001 to 2003, the estimates of β_{soe*t} are not significantly different in the regressions of input prices and TFP. This suggests that SOEs and non-SOEs had a common trend in input prices and TFP before SASAC. As a result, the critical common pre-trend assumption for the difference-in-differences approach is satisfied, at least for the regressions using input prices and TFP. The estimates of β_{soe*t} for productivity, however, show a slight growing trend before SASAC. From 2001 to 2003, the productivity gap was reduced by about 4% in total, with an average annual change of around 2%. Nonetheless, this is much smaller than the significant jump in productivity in 2004 (about 9% in a single year) when SASAC took effect. This sharp comparison suggests a strong differential impact of SASAC on SOEs and non-SOEs, which lends us the power to identify the impact of external monitoring on productivity even when there is a slight pre-trend in productivity before the treatment.[23]

4.3 Role of Monitoring Costs: Spatial Dimension Evidence

To strengthen the causality result between monitoring and SOE performance, we test the impact of monitoring costs on firm performance in the spatial dimension and examine how the strengthened monitoring by SASAC heterogeneously influences the input prices and productivity of SOEs.

4.3.1 Monitoring Costs and SOE Performance

If external monitoring from the oversight government matters for SOE performance, then larger monitoring costs, which imply lower monitoring strength, would lead to more managerial expropriation and shirking and, as a result, weaker performance, as predicted by the stylized model in Online Appendix C. We examine this conjecture in this subsection.

Chinese SOEs, by registration, are affiliated to and overseen by one of the following government levels:

[23] To further ensure that the results are not driven by the differential pre-trend (especially for productivity), we remove the potential pre-trend and re-estimate the regression specifications in the robustness check in Online Appendix G.6. After detrending, all the major results are very similar to the baseline results, qualitatively and quantitatively.

central, province, or municipality (or prefecture).[24] We proxy the monitoring costs by the physical distance (in logarithm) of an SOE to its oversight government (*oversight distance* henceforth, for short). In the literature, distance has been documented to have significant consequences for firms. To analyze the determinants of the government's decision to decentralize SOEs, Huang et al. (forthcoming) document that information asymmetry and monitoring difficulties between SOEs and the oversight government increase in the physical distance between them. Consistent with their insight, in our context, greater oversight distance implies weaker monitoring of SOEs' managerial effort by their oversight government, leading to a higher level of managerial expropriation and shirking. Bloom et al. (2012) also show that distance helps to explain the decentralization decision between multinational headquarters and overseas subsidiaries.

One potential concern is that the distance measure may contain more information than just monitoring costs. For example, because oversight governments are usually located in large cities, the distance to the oversight government may reflect agglomeration and localized material prices. Fortunately, non-SOEs are also registered to be affiliated to one level of government exactly in the same way as the system for SOEs. The difference is that the affiliated government is responsible for supervising and monitoring the SOEs' performance, but it bears no responsibility for monitoring the performance of affiliated non-SOEs. Such difference helps us to identify the effect of distance as a proxy for monitoring costs separate from the effects of agglomeration and localization. In light of this, we calculate the distance of non-SOEs to their affiliated government in the same way as that of SOEs, and add the distance measure and its interaction with the SOE dummy in the regression. While other factors (i.e., agglomeration and localization) affecting SOEs and non-SOEs similarly are controlled by the distance variable, the monitoring effect is identified by the interaction between SOEs and oversight distance.[25]

Specifically, we estimate the following baseline specification to analyze the impact of monitoring costs:

$$Y_{jt} = \beta_0 + \beta_{soe} SOE_{jt} + \beta_{soe*dist} \left(SOE_{jt} * Dist_{jt} \right) + \beta_{dist} Dist_{jt} + \beta_z Z_{jt} + \lambda_{ind} + \lambda_{prov} + \lambda_t + \varepsilon_{jt}, \quad (24)$$

where $Dist_{jt}$ represents the oversight distance.[26] We are particularly interested in the parameter

[24] In general, a detailed classification of government levels is central, province, municipality (or prefecture), county, and township. Nonetheless, the de facto supervision and monitoring of SOEs mainly come from the municipality-level governments or higher. That is, for SOEs registered to be overseen by the county-level government or lower, they are usually overseen by the municipality government indirectly, so we treat them as being supervised by the municipality government.

[25] In the data, many of the firms are recorded as "others" in the affiliated government column. They include three types of firms: (1) subsidiary firms founded and owned by other legal bodies, (2) firms without an affiliated government, and (3) subsidiary firms founded and owned by non-centrally-affiliated firms or legal bodies from other provinces. We do not observe the affiliation of these firms to their founding firms/organizations. It is also unclear how cross-province operations would affect firm performance. As a result, we drop these observations in all regressions that use oversight distance. After this treatment, we have a sample of 541,117 observations.

[26] The distance measure, $Dist_{jt}$, is indexed by firm j and year t. This is because in the data we observe that around 1% of non-SOEs and 8% of SOEs changed distance due to decentralization (as analyzed in Huang et al., forthcoming) or relocation. We tested our regressions with a subsample that excludes these firms, and the results are quantitatively and

Table 4: *Monitoring Costs and the Performance of SOEs*

	(1) Input price	(2) Input price	(3) Productivity	(4) Productivity	(5) TFP	(6) TFP
Panel A: Baseline Specification						
SOE	0.062***	0.060***	-0.189***	-0.169***	-0.165***	-0.157***
	(0.002)	(0.001)	(0.008)	(0.006)	(0.005)	(0.005)
SOE*Dist	0.002***	0.001***	-0.011***	-0.006***	0.001	0.002
	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)
Dist	YES	YES	YES	YES	YES	YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity		YES		YES		YES
Observations	541,117	392,900	541,117	392,900	541,117	392,900
Adjusted R^2	0.946	0.970	0.928	0.966	0.669	0.707
Panel B: Full Specification with Heterogeneous SASAC Effect						
SOE	0.067***	0.064***	-0.222***	-0.196***	-0.175***	-0.165***
	(0.002)	(0.001)	(0.009)	(0.007)	(0.005)	(0.005)
SASAC*SOE	-0.026***	-0.019***	0.141***	0.096***	0.051***	0.035***
	(0.003)	(0.002)	(0.013)	(0.010)	(0.008)	(0.008)
SOE*Dist	0.005***	0.003***	-0.014***	-0.007***	-0.004**	-0.004**
	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)	(0.002)
SASAC*SOE*Dist	-0.007***	-0.005***	0.008**	0.003	0.015***	0.015***
	(0.001)	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)
SASAC*Dist	YES	YES	YES	YES	YES	YES
Dist	YES	YES	YES	YES	YES	YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity		YES		YES		YES
Observations	541,117	392,900	541,117	392,900	541,117	392,900
Adjusted R^2	0.946	0.970	0.928	0.966	0.669	0.708

Standard errors (clustered at the firm level) are in parentheses.
Constant and fixed effects of province, year, industry, and registration affiliation are included in all the regressions.
* $p < .10$, ** $p < .05$, *** $p < .01$

$\beta_{soe*dist}$, which captures the impact of monitoring costs on SOEs' performance.

Furthermore, similar to Huang et al. (forthcoming), who find that the government tends to decentralize SOEs that are far away, SASAC may have an incentive to exert a greater level of monitoring strength on SOEs that were far away and had weaker performance. As a result, the establishment of SASAC can generate heterogeneous impact: SOEs that were far away from their oversight government improve more in input prices and productivity after SASAC. To take this into account, we estimate the full

qualitatively similar. The results are available upon request.

specification:

$$
\begin{aligned}
Y_{jt} &= \beta_0 + \beta_{soe} SOE_{jt} + \beta_{soe*dist}\left(SOE_{jt} * Dist_{jt}\right) + \beta_{soe*sasac}\left(SOE_{jt} * SASAC_t\right) \\
&\quad + \beta_{soe*dist*sasac}\left(SOE_{jt} * Dist_{jt} * SASAC_t\right) + \beta_{dist*sasac}\left(Dist_{jt} * SASAC_t\right) \\
&\quad + \beta_{dist} Dist_{jt} + \beta_z Z_{jt} + \lambda_{ind} + \lambda_{prov} + \lambda_t + \varepsilon_{jt}. \qquad (25)
\end{aligned}
$$

The parameter of interest, $\beta_{soe*dist*sasac}$, captures the impact of SASAC on SOEs at different oversight distances.[27] We also control for the possibility that factors (such as agglomeration and localized markets) contained in the distance measure may affect firms differently after SASAC, using $Dist_{jt} * SASAC_t$.

The results are reported in Table 4. In both specifications, we find that monitoring costs (as proxied by oversight distance) matter for SOEs' performance. As characterized by the coefficients of $SOE * Dist$, oversight distance increases SOEs' input prices and reduces their productivity. Doubling the oversight distance increases input prices paid by SOEs by 0.3% and reduces SOEs' productivity by 0.7% before the establishment of SASAC, relative to non-SOEs. These findings support the conjecture that higher monitoring costs for distant SOE firms reduce external monitoring of firm management and lead to expropriation and shirking in production and input procurement.

Moreover, the estimates of $\beta_{soe*dist*sasac}$ show a heterogeneous impact of SASAC on SOEs that are with different distances to their oversight government. The negative sign of $\beta_{soe*dist*sasac}$ in the input price regression and the positive sign in the productivity regression reflect that the gaps in input prices and productivity between SOEs of different oversight distances are narrower after the establishment of SASAC. When using the traditional TFP as a measure of firm performance, we find even stronger results. This shows that SASAC had heterogeneous impact on SOEs and significantly alleviated the negative role of monitoring costs in firm performance. This finding is intuitive. First, SOEs that were far from their oversight government had weaker performance than those that were closer before SASAC. As a result, they have larger potential gains when monitoring is strengthened. Second, knowing that distinct SOEs had more serious monitoring problems, SASAC might have implemented a higher degree of monitoring of SOEs that were far away. Both of these reasons may contribute to the reduction in the gap between distant SOEs and closer SOEs after SASAC.

Although the establishment of SASAC was the main and largest policy shock for SOEs during the data period, it was accompanied by several other contemporaneous policy measures, which may confound our results. We show that our results are robust after controlling for these contemporaneous policy measures as follows. First, SOEs may face friction in firing redundant labor and such friction may decrease over time (e.g., Hsieh and Song, 2015; Berkowitz et al., 2017). In Online Appendix E, we model how

[27] In Online Appendix G, we show that the results are robust after considering privatization, market competition, SOE privilege enhancement, entry/exit, alternative definitions of SOEs, firm fixed effects, and international trade participation.

labor friction could influence the estimates of input prices and productivity, and we empirically show that the influence is quantitatively negligible in our application. Second, Chinese SOEs experienced a significant wave of restructuring and privatization (e.g., Hsieh and Song, 2015), led by the policy "grasp the large and let go of the small" starting in the 1990s: large SOEs were corporatized and merged into large industrial groups under the control of the Chinese state ("grasp the large") and small SOEs were privatized or closed ("let go of the small"). In Online Appendix G, we conduct three exercises to show that the monitoring effect is not driven by restructuring or privatization, by dropping privatized firms or potentially restructured SOEs, focusing on non-pillar industries in which restructuring was less likely to happen, and distinguishing SOEs of different levels respectively. Third, the Chinese government might have sought to maintain the dominance and market power of SOEs (usually labeled as "state capitalism"), especially in pillar industries. If SOEs' market power in the product and input markets increased over time, our estimated SASAC effect could be contaminated. Online Appendix G conducts careful exercises to ensure that the monitoring effect is not driven by the potential changes in market power in the input/output markets. Finally, we provide detailed evidence in Online Appendix G to show that our results are robust after controlling for potential differential trends between SOEs and non-SOEs, using a balanced panel, adopting an alternative definition of SOEs following Hsieh and Song (2015), controlling for firm fixed effects, accounting for China's access to the WTO, and accounting for firms' trade participation.

4.3.2 Mechanism That Makes Oversight Distance Matter

In this subsection, we explore the mechanism through which oversight distance matters by examining the role of travel difficulty from oversight governments to SOEs. We also control for the distance to non-oversight large cities to tease out the role of oversight distance as proxy for monitoring costs.

We start by considering an alternative distance measure, road distance ("RoadDist"), which is defined as the shortest road transportation distance between a firm and its affiliated government. This definition is based on the major road network according to the "National Roads and Highways of China", which covers national highways, provincial highways, and other major roads. The shortest road distance reflects the combined effects of three factors that influence travel time: the direct (spherical) distance, local geographic landscape, and road infrastructure. As a result, it is a reasonable measure of transportation costs.[28] The way that SASAC operates suggests that the physical interaction of

[28] We use the 2009 version of "National Roads and Highways of China", which is the first year available to us. The shortest road distance is a more reasonable measure of transportation costs compared with the direct distance and local geographic conditions for two reasons. First, when building roads, the engineers typically try to optimize to minimize the transportation costs given geographic conditions (e.g., mountains and rivers). Second, when calculating the distance, we take into account the multiple choices of available roads and minimize the travel distance given the road infrastructure. The correlation between the road distance and the direct distance is 0.65.

government officials and SOEs is the major mechanism that makes distance matter. If this conjecture is correct, then the regression results based on the road distance should be even stronger than our baseline results when direct (spherical) distance is used. We confirm this conjecture in the left panel of Table 5, contrasting the results with the baseline results in Table 4. The SASAC effect on SOEs of different distances still remains robust.

Table 5: *SASAC and SOE Performance: Road Distance and Travel Difficulty*

	(1)	(2)	(3)	(4)	(5)	(6)
	Input price	Productivity	TFP	Input price	Productivity	TFP
SOE	0.060***	-0.188***	-0.152***	0.063***	-0.186***	-0.161***
	(0.002)	(0.011)	(0.009)	(0.002)	(0.008)	(0.006)
SASAC*SOE	-0.018***	0.087***	0.022*	-0.019***	0.087***	0.031***
	(0.003)	(0.015)	(0.013)	(0.002)	(0.011)	(0.010)
SOE*RoadDist	0.004***	-0.008***	-0.006***			
	(0.001)	(0.003)	(0.002)			
SASAC*SOE*RoadDist	-0.005***	0.005	0.015***			
	(0.001)	(0.003)	(0.003)			
SOE*Dist				0.004***	-0.008***	-0.003*
				(0.001)	(0.002)	(0.002)
SASAC*SOE*Dist				-0.006***	0.006**	0.017***
				(0.001)	(0.003)	(0.003)
SOE*Dist*TraDiff				0.003***	-0.014***	-0.007*
				(0.001)	(0.003)	(0.004)
SASAC*SOE*Dist*TraDiff				0.001	0.005	-0.006
				(0.001)	(0.004)	(0.004)
SASAC*RoadDist	YES	YES	YES			
RoadDist	YES	YES	YES			
SASAC*Dist				YES	YES	YES
Dist				YES	YES	YES
Other TraDiff interactions				YES	YES	YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	314,665	314,665	314,665	314,530	314,530	314,530
Adjusted R^2	0.969	0.965	0.705	0.969	0.965	0.705

Standard errors are in parentheses.

Constant and fixed effects of province, year, industry, and registration affiliation are included in all the regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

To explore the mechanism further, we examine how travel difficulty between SOEs and their oversight governments influences SOE performance. We define travel difficulty ("TraDiff") as the ratio of the road distance to the direct (spherical) distance between a firm and its affiliated government. This measure captures the difficulty of traveling from the affiliated government to a firm, arising from geographic landscape and road infrastructure development, given the direct (spherical) distance. We find that, conditional on the direct distance, travel difficulty substantially increases SOEs' input prices and reduces productivity (relative to non-SOEs), as represented by the coefficient of "SOE*Dist*TraDiff" in the right panel of Table 5. This supports the physical interaction of government officials with SOEs as a mechanism for distance to matter. In addition, all the other coefficient estimates are very close to the results in Table 4. The insignificant effect of SASAC on SOEs of different travel difficulties may reflect the combined effect of two offsetting factors. On the one hand, travel difficulty reduces the monitoring effectiveness of SASAC; on the other hand, SASAC may purposely exert stronger monitoring on SOEs with larger travel difficulty.

As an alternative strategy to examine the mechanism and tease out the role of external monitoring, we control for SOEs' distance to the largest city ("Dist2") other than the city of the oversight government in the area. This non-oversight distance helps to control for spatial related factors such as agglomeration and localized material prices (other than monitoring costs) that may influence the performance difference between SOEs and non-SOEs. Therefore, the differential effect of the oversight distance and non-oversight distance identifies the effect of monitoring costs arising from oversight distance. Specifically, we estimate the following regression model:

$$\begin{aligned} Y_{jt} \;=\;& \beta_0 + \beta_{soe} SOE_{jt} + (\beta_{soe*dist} + \beta_{soe*dist2})\,(SOE_{jt} * Dist_{jt}) + \beta_{soe*dist2}\,(SOE_{jt} * Dist2_{jt}) \\ & + \beta_{dist} Dist_{jt} + \beta_{dist2} Dist2_{jt} + \beta_z Z_{jt} + \lambda_{ind} + \lambda_{prov} + \lambda_t + \varepsilon_{jt}. \end{aligned} \tag{26}$$

As shown in the left panel of Table 6, the differential effect ($\beta_{soe*dist}$) is significant economically and statistically, with larger oversight distance resulting in higher input prices and lower productivity.[29] This result suggests that external monitoring plays a role and distance-related monitoring costs influence SOE performance, even after controlling for potentially different effects of spatial-related factors (such as agglomeration) on SOEs and non-SOEs.

Similarly, we estimate the following augmented model of the SASAC monitoring effect after controlling for non-oversight distance. The model allows that spatial-related factors have different effects on SOEs and non-SOEs and these factors may change over time.

$$\begin{aligned} Y_{jt} \;=\;& \beta_0 + \beta_{soe} SOE_{jt} + \beta_{soe*sasac}\,(SOE_{jt} * SASAC_t) + (\beta_{soe*dist} + \beta_{soe*dist2})\,(SOE_{jt} * Dist_{jt}) \\ & + (\beta_{soe*dist*sasac} + \beta_{soe*dist2*sasac})\,(SOE_{jt} * Dist_{jt} * SASAC_t) \\ & + \beta_{soe*dist2}\,(SOE_{jt} * Dist2_{jt}) + \beta_{soe*dist2*sasac}\,(SOE_{jt} * Dist2_{jt} * SASAC_t) \\ & + \beta_{Inter} InteractionDist_{jt} + \beta_z Z_{jt} + \lambda_{ind} + \lambda_{prov} + \lambda_t + \varepsilon_{jt}, \end{aligned} \tag{27}$$

where $InteractionDist_{jt}$ represents all other interactions between $Dist_{jt}$, $Dist2_{jt}$, and other terms. The parameter of interest, $\beta_{soe*dist*sasac}$, measures the differential effect of SASAC on SOEs of different monitoring costs. The results in the right panel of Table 6 show that our baseline results are robust:

[29] The estimated effect of oversight distance is even larger after controlling for the non-oversight distance. One potential explanation is that non-SOEs may benefit more from agglomeration compared with SOEs, so the performance gap is smaller in distant areas where there is lower agglomeration.

Table 6: *Role of Monitoring Costs: Control for Non-Oversight Distance*

	(1) Input price	(2) Productivity	(3) TFP	(4) Input price	(5) Productivity	(6) TFP
SOE	0.084***	-0.229***	-0.188***	0.095***	-0.276***	-0.210***
	(0.003)	(0.013)	(0.011)	(0.003)	(0.014)	(0.012)
SASAC*SOE				-0.044***	0.171***	0.092***
				(0.005)	(0.020)	(0.018)
SOE*Dist	0.007***	-0.011***	-0.004	0.011***	-0.019***	-0.015***
	(0.001)	(0.004)	(0.003)	(0.001)	(0.004)	(0.003)
SASAC*SOE*Dist				-0.014***	0.033***	0.038***
				(0.001)	(0.006)	(0.005)
Dist Interactions	YES	YES	YES	YES	YES	YES
Dist2 Interactions	YES	YES	YES	YES	YES	YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	270,414	270,414	270,414	270,414	270,414	270,414
Adjusted R^2	0.970	0.967	0.698	0.970	0.967	0.699

The estimate of $\beta_{soe*dist}$ is presented by SOE*Dist, and $\beta_{soe*dist*sasac}$ is presented by SASAC*SOE*Dist.
Standard errors are in parentheses.
Constant and fixed effects of province, year, industry, and registration affiliation are included in all the regressions.
* $p < .10$, ** $p < .05$, *** $p < .01$

SASAC results a greater improvement of SOEs with higher monitoring costs (which performed worse before SASAC) in terms of input prices and productivity.[30]

Overall, these results support that the physical interaction of SOEs with government officials is a mechanism for distance to matter and that SASAC has weakened the resistance to monitoring created by physical distance.

4.4 Implications for Aggregate Productivity and Input Misallocation

The above analysis suggests that, at the firm level, ineffective external monitoring is responsible for weak SOE performance, and strengthened monitoring can promote firm performance via the channels of input prices and productivity. A natural question is how does this matter at the aggregate level? To shed light on this question, we evaluate the impact of the establishment of SASAC and monitoring costs on aggregate productivity and input prices, as well as their implication for reducing intermediate input misallocation across firms. Because the parameter estimates are based on the difference-in-differences analysis, we cannot calculate the overall level effect of external monitoring. Instead, we evaluate the

[30]The estimated SASAC effect is quantitatively larger after using non-oversight distance to control for the changes of other factors, such as evolution of agglomeration and local market conditions. One possibility is that due to the improvement of transportation conditions over time, more distant areas are integrated and firms in those areas can benefit more from agglomeration as a result. If non-SOEs benefits more from agglomeration, then more agglomeration reduces the performance gaps between SOEs and non-SOEs in distant areas in a larger magnitude. Thus, without controlling for this factor, we underestimate the effect of the SASAC on distant SOEs. Controlling for this factor corrects this bias, resulting in a greater effect of the SASAC on distant SOEs.

Table 7: *Impact on Aggregate Input Prices and Productivity (%)*

	Input Price	Productivity	TFP
Panel A: Impact of SASAC			
SOEs	-3.97	10.84	9.72
Manufacturing Sector	-0.51	1.39	1.24
Panel B: Impact of Monitoring Costs			
SOEs	1.15	-2.67	-1.53
Manufacturing Sector	0.20	-0.46	-0.26

[1] Panels A and B show the impact of SASAC and monitoring costs, respectively, on the sales-weighted average of input prices, productivity, and TFP of SOEs as well as all firms in the manufacturing sector (e.g., covering both SOEs and non-SOEs).

aggregate impact of removing the SASAC effect for SOEs (or the monitoring cost effect) while keeping input prices and the productivity of non-SOEs fixed.

First, to understand the aggregate impact of SASAC on SOEs as well as the entire manufacturing sector, we consider a counterfactual scenario where the effect of SASAC on SOEs is removed. SASAC has heterogenous impact on SOEs depending on their distances to monitoring governments. Thus, in the counterfactual scenario, we remove $\hat{\beta}_{soe*sasac}SASAC_t * SOE_{jt}$ and $\hat{\beta}_{soe*dist*sasac}SASAC_t * SOE_{jt} * Dist_{jt}$ (both estimated from (25)) from the input prices, productivity, and TFP of all SOEs, respectively. Then we compare the revenue-weighted aggregate values in the data with the counterparts computed from the counterfactual scenario. Panel A in Table 7 shows that, as an SOE-exclusive policy, the relative effect of SASAC on SOEs has significantly reduced the aggregate input price of SOEs by 3.97%, and increased aggregate productivity and TFP by 10.84% and 9.72%, respectively.[31] Accordingly, the overall aggregate input price of the entire manufacturing sector is reduced by 0.51%, and aggregate productivity and TFP are increased by 1.39 and 1.24%, respectively.[32]

Second, to gauge the aggregate impact of the monitoring costs arising from geographic oversight distance, we consider a counterfactual scenario where the oversight distance is zero. That is, we subtract $\hat{\beta}_{soe*dist}Dist_{jt} * SOE_{jt}$ (estimated from (25)) from the input prices, productivity, and TFP of all SOEs, respectively. Then we compare the sales-weighted aggregate values with the counterparts

[31] The productivity effect is about twice as large as that estimated in Berkowitz et al. (2017), who show that the productivity gap between SOEs and other firms shrinks by 5.4% before and after 2003, using a traditional productivity measure without considering input price heterogeneity and the heterogeneous impacts on SOEs with geographic differences. Hsieh and Song (2015) show that the weighted average TFP (as traditionally defined) of surviving state-owned firms relative to that of surviving private firms increased from 55% to 75%.

[32] These changes do not include possible production reallocation across firms, in particular between SOEs and non-SOEs, because we keep the same revenue weight in the aggregation. However, the reallocation between the two groups of the firms is fairly weak (only accounting for 6% of the overall growth) for productivity and negative for input prices and TFP. This suggests that these documented changes are likely to be lower bounds of the actual impact.

from the data. The results are presented in Panel B in Table 7. Within the group of SOEs, the monitoring costs increase the aggregate input price by 1.15%, and reduce aggregate productivity and TFP by 2.67% and 1.53%, respectively. As a result, the overall aggregate input price for the entire manufacturing sector is increased by 0.20%, and aggregate productivity and TFP are reduced by 0.46% and 0.26%, respectively.

The above analysis has important implications for intermediate input misallocation. In principle, input misallocation (or distortion) is usually modeled by the difference between the marginal revenue product of an input and the input price (e.g., Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). In our context, there is a large input price gap between SOEs and their non-SOE counterparts, implying misallocation in intermediate inputs. The analysis shows that strengthened external monitoring can improve the input prices of SOEs and reduce the gap by 52%, which suggests an improvement in allocative efficiency of intermediate inputs.[33] Compared with the literature that focuses on misallocation arising from political connections, informational frictions, and geographical access (e.g., Faccio, 2006; Bloom et al., 2013; David et al., 2016; Singer, 2019), we contribute by showing that ineffective external monitoring is a source of misallocation of intermediate inputs.

5 Conclusion

Effective external monitoring is an indispensable part of corporate governance to enhance firm performance by reducing shirking and managerial expropriation. This paper empirically investigates how strengthened external monitoring by the government can affect SOE performance, through the channels of intermediate input prices and productivity, in the context of Chinese SOEs. We first document that overall, SOEs pay 6.4% higher input prices and their productivity is about 20% lower, compared with their non-SOE counterparts. We provide evidence of the impact of external monitoring on SOE performance, using variations across the time and spatial dimensions. In the time dimension, the establishment of SASAC, by strengthening monitoring of SOEs exclusively, substantially narrowed the gaps between SOEs and non-SOEs in input prices and productivity by around half. In the spatial dimension, SOEs with higher monitoring costs, as proxied by the distance of SOEs to their own oversight government, pay relatively higher input prices and have lower productivity. Such negative impact was largely mitigated by strengthened government monitoring after SASAC. These firm-level effects have significant impacts on aggregate productivity and input price levels, for SOE firms and all firms as a whole.

The results corroborate the findings of studies that document significant gaps between SOEs and non-SOEs, and contribute to the long-standing debate on how to improve SOE performance through

[33] This is calculated as 3.97 (impact of SASAC from Table 7) divided by 7.6 (the gap before SASAC from Table 3).

public policy. The results suggest that enhancement of government monitoring and credible punishment can serve as effective policy instruments to improve SOE performance, even without ownership change (privatization), massive capital investment, or layoff of workers. This is important for police makers, especially in industries that cannot be privatized due to economic or political reasons.

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Additional Supporting Information may be found in the online version of this article:

Online Appendix
Replication Package

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Supplementary Materials for "Does External Monitoring from Government Improve the Performance of State-Owned Enterprises?"

by Shengyu Li and Hongsong Zhang

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This appendix provides more detailed description of SASAC and its strengthened monitoring on SOEs in Appendix A, and more details on the model in Appendix B and C. It also includes a wide range of robustness analysis and checks to ensure that the main results are not contaminated by other driving forces in the data period. Overall, our main results are very robust to these checks.

A Detailed Description of SASAC Monitoring

In this section, we provide more descriptive evidence of "SASAC monitoring" from the following aspects: the regulation, organization, actions taken, and outcomes. A summary of the main functions of SASAC is given in Table OA1.

Regulations. Following the establishment of SASAC at the central and local level, it announced a series of policies and regulations of its practices.[34] These policies and regulations clearly define the responsibilities and measures that SASAC should take to supervise and monitor SOEs. Monitoring business operation, improving operation efficiency, and anti-corruption in transactions are among the most important focuses of SASAC's purposes. For example, in the "Opinions on strengthening the Supervision and Monitoring of Central SOEs' Efficiency" effective in 2004, it clearly stated that SASAC and the SOEs' supervision unit should work together to *"...supervise and monitor the management activities of the supervisee (SOEs top managers), supervise and monitor the SOEs' management efficiency and effectiveness, and correct and punish any illegal activities in SOEs' production and management process".* Importantly, the local SASAC at the province and city-level governments implemented similar policies, sometimes with slight modification to cater to the local industry characteristics.

Organizations. SASAC established a special department, the "Supervision Bureau", which is dedicated to supervising and monitoring the operation of SOEs. On top of that, the Central Commission

[34]Representative policies and regulations include the "Policies, Laws and Regulations: Decree of the State Council of the People's Republic of China. No. 378" effective in 2003, the "Opinions on strengthening the Supervision and Monitoring of Central SOEs' Efficiency" effective in 2004, and the "Interim Measures for the supervision and Monitoring of Central SOEs" effective in 2006. Following central SOEs, the local SASAC at the province and city-level implemented similar measures on SOEs affiliated to them (sometimes with slight modifications).

for Discipline Inspection and National Supervisory Committee set up an in-house bureau in the central SASAC, named "SASAC Discipline Inspection and Supervision Bureau", to work directly in SASAC to strengthen the monitoring of top managers against malfeasance and corruption. Similar organizations are established at the local level SASAC offices accordingly.

At the same time, SASAC required SOEs to establish the "Efficiency Supervision and Monitoring Unit", which is responsible for implementing the policies and regulations of SASAC in order to strengthen the monitoring of operations and transactions in SOEs. This unit is supervised and guided by the "SASAC Discipline Inspection and Supervision Bureau" and "Supervision Bureau". They work together to monitor the SOE to reduce wrongdoings and improve efficiency.

Actions. In accordance with the regulations, SASAC took a series of actions to improve the monitoring on SOEs' operation and transactions, including improving the assessment criteria and index system, dispatching supervisory panels to SOEs regularly and randomly to supervise SOEs' daily operation, more direct participation in formulating the operational budgets and final accounts of SOEs, and helping to establish the "Efficiency Supervision and Monitoring Unit" and work with it to improve SOE performance.

Outcomes. These strong monitoring actions yielded fruitful outcomes. In addition to the examples provided in the paper in Section 2.2, the cases in other provinces and cities also strongly support the monitoring achievement of SASAC wherever we have data. For instance, in *Jiang Shu*, the province-level SASAC investigated 787 cases and punished 93 SOE managers and associated government officials, recovering direct economic losses of 1.5 billion RMB (0.19 billion USD) in 2004. In 2006, the city-level SASAC in *Shen Zhen* investigated 18 cases that violated the law and recovered direct economic losses of 750 million RMB (94 million USD). Overall, the measures taken by SASAC directly strengthened the external monitoring on SOEs.

Table OA1: Main Functions of SASAC

Summary	**Detailed Functions of SASAC**
1. Performs investor's responsibilities	Performs investor's responsibilities, supervises and manages the state-owned assets of the enterprises under the supervision of the central government (excluding financial enterprises), and enhances the management of state-owned assets.
2. Implementable measures to ensure preservation and increment of the value of the state-owned assets	Establishes and improves the index system of the preservation and growth of the value of state-owned assets, and works out assessment criteria; supervises and administers the preservation and growth of the value of the state-owned assets of the supervised enterprises through statistics and auditing; and is responsible for the management work of wages and remuneration of the supervised enterprises and formulates policies regulating the income distribution of the top executives of the supervised enterprises and organizes implementation of the policies.
3. SOE reform and establishment of modern enterprise system	Guides and pushes forward the reform and restructuring of state-owned enterprises, advances the establishment of modern enterprise system in SOEs, improves corporate governance, and propels the strategic adjustment of the layout and structure of the state economy.
4. On top executives of SOE	Appoints and removes the top executives of the supervised enterprises, and evaluates their performances through legal procedures and either grants rewards or inflicts punishments based on their performances; establishes corporate executives selection system in accordance with the requirements of the socialist market economy system and modern enterprise system, and improves incentives and restraints system for corporate management.
5. Dispatches supervisory panels to monitor SOE	In accordance with related regulations, SASAC dispatches supervisory panels to the supervised enterprises on behalf of the state council and takes charge of daily management of the supervisory panels.
6. SOE operational budget, final account, and capital gains	Organizes the supervised enterprises to turn the state-owned capital gains over to the state, participates in formulating management system and methods of the state-owned capital operational budget, and is responsible for working out the state-owned capital operational budget and final account and their implementation in accordance with related regulations.
7. Ensures SOEs to obey laws and safety production	Urges the supervised enterprises to carry out the guiding principles, policies, related laws and regulations and standards for safety production and inspects the results in accordance with the responsibilities as investor.
8. Draft laws, regulations, and rules	Responsible for the fundamental management of the state-owned assets of enterprises, works out draft laws and regulations on the management of the state-owned assets, establishes related rules and regulations and directs and supervises the management work of local state-owned assets according to law.
9. Other tasks	Undertakes other tasks assigned by the State Council.

Source: Official website of the State Asset Supervision and Administration Commission of the State Council, the People's Republic of China.

B Effective Material Services

Our empirical structural model captures the effect of material quality through the input-output quality linkage. However, the material quality may also have an impact by augmenting the effective services provided by materials. That is, higher quality material may provide more material services, which contributes more to production. This section considers an alternative model with both the input-output quality linkage and the effective material services effect. We show that this alternative model is equivalent to our model (with only input-output quality linkage) for the purpose of this study. In particular, the alternative model generates the same estimates of quality-adjusted material prices and productivity as in the main model. It only affects the interpretation of the estimates of the quality-inclusive material prices. That is, if there are both input-output quality linkage and the effective material services effect, the quality-inclusive material input price ($\tilde{p}_{Mjt}$) estimated in our main model is a price measure that is adjusted by the effective material services effect.

Setup and Assumptions. We consider the following generalized production function:

$$\tilde{Q}_{jt} = \tilde{\Omega}_{jt} F(L_{jt}, M_{jt}, K_{jt}) \quad = \quad \tilde{\Omega}_{jt} \left[\alpha_L L_{jt}^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma} \right]^{\frac{1}{\gamma}}, \tag{28}$$

where the effective *material services* $M_{jt} = \Psi(H_{jt}) M_{0jt}$. So M_{0jt} physical units of material quantity of quality H_{jt} can provide M_{jt} units of material services. Thus the new production function allows input quality to have an impact through the input-output quality linkage via $\tilde{\Omega}_{jt}$ and the effective material services effect via $\Psi(H_{jt})$. If $\Psi(H_{jt}) = 1$, then this new production function degenerates to that in our main model exactly.

Assume that the unit price of *material services* is

$$\tilde{P}_{Mjt} = P_{Mjt} H_{jt}, \tag{29}$$

which is the same as as the pricing equation (5) in our main model. The expenditure to purchase $M_{jt} = \Psi(H_{jt}) M_{0jt}$ units of material services, or equivalently M_{0jt} units of material, is $E_{Mjt} = \tilde{P}_{Mjt} M_{jt}$ by definition. Thus, Eq. (29) implies that the unit price of physical material is $\tilde{P}_{0Mjt} = \frac{E_{Mjt}}{M_{0jt}} = \frac{(P_{Mjt} H_{jt}) M_{jt}}{M_{jt}/\Psi(H_{jt})} = P_{Mjt} \Psi(H_{jt}) H_{jt}$. Intuitively, the impact of quality on the unit price of physical material captures both the effective material service effect via $\Psi(H_{jt})$ and the input-output quality linkage via H_{jt}.

All other model components remain the same as in our main model, including demand function, firm capability $\tilde{\Omega}_{jt}$, and the evolution processes of productivity and material price, as specified in Eq. (1), (3), (4), and (6), respectively.

After observing its capital stock, productivity, quality-adjusted input prices (P_{Mjt}), and wage rate (P_{Ljt}), each firm maximizes its profit by choosing the quantity of labor and material, material quality, and output:

$$\begin{aligned} \pi(P_{Mjt}, \omega_{jt}, K_{jt}, P_{Ljt}) = \max_{L_{jt}, M_{0jt}, \tilde{Q}_{jt}, H_{jt}} \quad & P_{jt}\tilde{Q}_{jt} - \tilde{P}_{0Mjt}M_{0jt} - P_{L_{jt}}L_{jt}, \\ \text{subject to:} \quad & (1),\ (28) \text{ and } (29). \end{aligned} \tag{30}$$

Note that here the firm chooses the material quantity M_{0jt} to maximize its profit. However, if $\Psi(H_{jt}) = 1$, then this maximization problem degenerates to that in our main model.

Equivalence Result. We can show that this alternative model is equivalent to our main model empirically for our purpose, by rewriting everything in the units of material services (M_{jt}) instead of material quantity (M_{0jt}).

First, it is straightforward that, when defined in the units of material services M_{jt} (instead of M_{0jt}), the production function in Eq. (28) is identical to that in the main model (Eq. (2)).

Second, in the units of material services (M_{jt}), the pricing function (29) is equivalent to that in our main model (Eq. (5)). Note that the price $\tilde{P}_{Mjt}$ in Eq. (29) is still quality-inclusive, because it does not adjust for the input-output quality linkage although it has accounted for effective material service effect.

As a result, in terms of material services (M_{jt}), the optimization problem defined in Eq. (30) is equivalent to Eq. (7) in our main model, except that now M_{jt} should be interpreted as the effective material services and $\tilde{P}_{Mjt}$ represents the price of the effective material services. Everything else in the main model holds exactly, including the first order conditions and the resulting estimation equations.

In sum, if the true model has both input-output quality linkages and effective material services effect, our main model with only input-output quality linkages still generates the same estimates of the quality-adjusted input prices (p_{Mjt}) and productivity (ω_{jt}), which are our main focus. All parameter estimates remain the same too. It only affects how we interpret the quality-inclusive material prices ($\tilde{p}_{Mjt}$) in our model. That is, if there are both input-output quality linkage and the effective material services effect, the quality-inclusive material input price ($\tilde{p}_{Mjt}$) estimated in our main model is a price measure that is adjusted by the effective material services effect.

C A Model of External Monitoring and Firm Performance

We describe a stylized theoretical model to demonstrate the mechanism through which the strength of external monitoring can create a specific type of distortion, by influencing a firm's input prices and productivity. We discuss broader possibilities of distortions and frictions faced by manufacturing firms and their implications to our econometric model in the end of this Appendix.

In the theoretical model, a firm makes two layers of decisions sequentially: first by a top manager and then by a production unit. The top manager chooses her efforts, which determine input prices and productivity. Then, observing the input prices and productivity, the production unit chooses quantities of labor and material to maximize firm profit. The top manager is self-interested and her choices are made to maximize her own payoff: her share of the firm profit (performance payment)[35] plus the kickback in material procurement, net of the costs of exerting the effort and the expected punishment for taking kickbacks, which depend on the strength of external monitoring.

Specifically, the top manager chooses two types of effort: procurement effort (e_M) and productivity effort (e_ω). Higher procurement effort helps the top manager to bargain for a better (lower) price for material inputs, which increases firm profits and thus increases her performance payment. Meanwhile, the top manager may take a kickback in the procurement, as a percentage (x) of the procurement value. If the manager bargains hard (exerting a high level of e_M) for lower input prices, she would get a lower kickback rate. That is, x is a function of e_M and $\partial x/\partial e_M < 0$). The manager may be caught and subject to punishment due to taking a kickback. It is natural to assume that the expected punishment for taking a kickback, $c(x(e_M), \theta)$, increases strictly in external monitoring strength θ and endogenous kickback rate x. At the same time, the productivity effort, e_ω, represents the effort the top manager exerts to improve production efficiency, by way of promoting firm culture or workers' morale. It directly affects the firm productivity. We assume that productivity (ω) increases in e_ω: $\partial\omega/\partial e_\omega > 0$. Both of these efforts incur the usual effort costs: $C_M(e_M)$ for procurement effort and $C_\omega(e_\omega)$ for productivity effort.[36]

Given the effort levels exerted by the top manager (thus p_M and ω), firm profit maximized by the production unit is denoted as $\pi(p_M(e_M), \omega(e_\omega))$, as will be discussed in Eq. (7) in Section 3.2, and the associated expenditure on material input as $E_M(p_M(e_M), \omega(e_\omega))$.[37] The top manager's maximization

[35] This includes the immediate payoff to the manager if the firm performs well, or future payoff in the broader forms of, for example, better career path etc. For easy reference, we simply call it performance payoff.

[36] To illustrate the idea, we assume that external monitoring incurs punishment only on procurement corruption, but not on shirking in productivity effort. This assumption is reasonable for two reasons. First, in practice it is much more difficult to detect and punish productivity shirking than procurement corruption. Second, the simplified model yields the same qualitative prediction on the impact of external monitoring on input prices and productivity, compared with an augmented model that also allows for punishment for productivity shirking.

[37] To highlight the impact of external monitoring, we ignore other determinants of profit for now.

problem is thus as follows:

$$\max_{\{e_M, e_\omega\}} \Pi(e_M, e_\omega) - C_M(e_M) - C_\omega(e_\omega) - C(e_M, \theta), \tag{31}$$

where the total payoff to the top manager from the performance payment and kickback is written as $\Pi(e_M, e_\omega) \equiv \pi(p_M(e_M), \omega(e_\omega)) + x(e_M)E_M(p_M(e_M), \omega(e_\omega))$,[38] and $C(e_M, \theta) \equiv c(x(e_M), \theta)$ is the expected punishment to the top manager for taking a kickback. We assume $\Pi''_{e_M e_M} < 0$, $\Pi''_{e_\omega e_\omega} < 0$ and $\Pi''_{e_M e_\omega} > 0$. That is, the total payoff function for the top manager has decreasing marginal returns to efforts and the two types of effort are complementary to promote the total payoff. We assume the effort cost functions as well as the corruption punishment function are convex with respective to the exerted effort: $C''_M > 0$, $C''_\omega > 0$, and $C''_{e_M e_M} > 0$. Importantly, we further assume $C''_{\theta e_M} < 0$. This is reasonable, because when external monitoring is stronger (i.e., larger θ), the marginal expected punishment is larger for lower e_M (thus higher corruption level x). Under these assumptions, we have the following proposition:

Proposition 1 (Impact of External Monitoring) *Stronger external monitoring increases both material procurement and productivity efforts, resulting in lower material input prices and higher productivity.*

Proof. To fix this idea, we focus on interior solution under regularity conditions, and assume all functions are differentiable up to second order whenever necessary.

The first-order conditions associated with the top manager's optimization problem (31) are:

$$e_M: \quad \Pi'_{e_M} - C'_M(e_M) - C'_{e_M}(e_M, \theta) = 0, \tag{32}$$

$$e_\omega: \quad \Pi'_{e_\omega} - C'_\omega(e_\omega) = 0. \tag{33}$$

Taking total differentiation of the first-order condition associated with e_ω with respect to θ yields

$$\Pi''_{e_M e_\omega} \frac{\partial e_M}{\partial \theta} + \left[\Pi''_{e_\omega e_\omega} - C''_\omega(e_\omega)\right] \frac{\partial e_\omega}{\partial \theta} = 0 \tag{34}$$

Given the assumptions on the total payoff function and the effort cost functions, we have $\Pi''_{e_M e_\omega} > 0$ and $\Pi''_{e_\omega e_\omega} - C''_\omega(e_\omega) < 0$ in Equation (34). As a result, we have

$$\text{sign}(\frac{\partial e_M}{\partial \theta}) = \text{sign}(\frac{\partial e_\omega}{\partial \theta}) \tag{35}$$

[38] To simplify the notation, we normalize the profit and cost functions by the profit share parameter in the performance payment to the top manager, so that firm profit share to the top manager now is 1 after normalization.

Similarly, taking total differentiation of the first-order condition associated with e_M with respect to θ, we have

$$\Pi''_{e_M e_\omega}\frac{\partial e_\omega}{\partial \theta} + \left[\Pi''_{e_M e_M} - C''_M(e_M) - C''_{e_M e_M}(e_M,\theta)\right]\frac{\partial e_M}{\partial \theta} \quad = \quad C''_{\theta e_M}(e_M,\theta). \tag{36}$$

Solving out $\frac{\partial e_\omega}{\partial \theta}$ from Equation (34) and replacing it in the above equation lead to

$$\left\{\frac{\Pi''_{e_M e_\omega}\Pi''_{e_M e_\omega}}{\left[\Pi''_{e_\omega e_\omega} - C''_\omega(e_\omega)\right]} + \left[\Pi''_{e_M e_M} - C''_M(e_M) - C''_{e_M e_M}(e_M,\theta)\right]\right\}\frac{\partial e_M}{\partial \theta} \quad = \quad C''_{\theta e_M}(e_M,\theta). \tag{37}$$

Since we have assumed $C''_{\theta e_M}(e_M,\theta) < 0$ and the term in the bracket on the left hand side is also negative. As a result, we have

$$\frac{\partial e_M}{\partial \theta} > 0.$$

Because $\text{sign}(\frac{\partial e_M}{\partial \theta}) = \text{sign}(\frac{\partial e_\omega}{\partial \theta})$ as shown above in Equation (35), we also have $\frac{\partial e_\omega}{\partial \theta} > 0$.

Because material prices decrease in procurement effort and productivity increases in productivity effort, firms facing stronger external monitoring on their management naturally have lower material prices and higher productivity. ■

The intuition is straightforward. Stronger external monitoring increases the expected punishment to corruption, which incentivizes the top manager to reduce procurement corruption (i.e., by increasing procurement effort). Although the external monitoring does not have a *direct* impact on productivity effort, it has an *indirect* impact: the complementarity between procurement and productivity efforts incentivizes the manager to increase productivity effort, as a response to the increased procurement effort induced by stronger external monitoring. As a result, both efforts are higher when external monitoring is stronger, and consequently, the firm pays lower material prices and has higher productivity.

Three predictions directly follow from Proposition 1. First, because SOEs faces lower external monitoring than non-SOEs, Proposition 1 implies that SOEs pay higher input prices and have lower productivity:

Conjecture 1 (SOE vs. non-SOE) *SOEs pay higher input price and have lower productivity compared with non-SOEs, other things being equal.*

Second, the establishment of SASAC directly improved the external monitoring on SOEs (but not on private firms), so we expect that SASAC has a positive impact on SOE performance in terms of productivity and input prices, relative to non-SOEs:

Conjecture 2 (SASAC Effect) *The establishment of SASAC reduced material input prices and* *increased productivity of SOEs, other things being equal.*

Moreover, if external monitoring does have an impact on SOE performance, then higher monitoring costs, which increase the difficulty of monitoring and thus reduce monitoring strength, serve as a barrier for SOE performance:

Conjecture 3 (Monitoring Costs and SOE Performance) *Higher monitoring costs reduce SOE performance, through the input prices and productivity channels, other things being equal.*

Discussion. This stylized theoretical model is one of possible ways to characterize the mechanism through which the strength of external monitoring can create distortions in individual firm's input prices and productivity. We emphasize that, conditional on input prices and productivity, the *production unit* of the firm makes optimal production decisions. However, *at the firm level*, such conditional-optimal decisions may not be optimal generally, due to the distortions in input prices and productivity within the firm and frictions in the market.

Bearing this spirit, our econometric model in Section 3.2 allows for potential distortions in capital, productivity, input prices, and wage rates across firms. This feature is important for the purpose of this study, because SOEs and non-SOEs (or even firms within each group generally) may differ substantially in their capital stock, productivity, and ability/incentive to secure better input prices. For example, SOEs may have better access to the financial market, leading to lower capital costs of SOEs relative to non-SOEs; some firms (SOEs or non-SOEs) may pay higher wage rates than other firms due to different reasons; firms facing different external monitoring strength, as the main focus discussed in this section, may differ substantially in their input prices and productivity. In the paper, we further discuss the detailed advantages of our econometric approach in Section 3.2.2 and show that its limitations are unlikely to affect our analysis.

D Flexible Labor Choice Assumption

The methodology to estimate productivity and input prices requires that the *production unit* of each firm chooses labor and material quantity to maximize profit, given firm productivity, input prices, and capital. Similar assumptions are commonly employed in a broad set of applications in related literature (e.g., Katayama et al., 2009; Epple et al., 2010; Gandhi et al., 2020; De Loecker, 2011; De Loecker and Warzynski, 2012; Zhang, 2019; Doraszelski and Jaumandreu, 2013). This Appendix provides evidence to show that this assumption is reasonable in the context of China during the sample period.

While flexible material choice is well accepted, the assumption of flexible labor choice is more controversial, especially in the United States and European countries with strong labor unions and high hiring/firing costs. In China, however, this is not an unrealistic assumption for several reasons. First, generally there is a lack of effectively-enforced laws and regulations to protect workers in China. This was especially true during the period (1998-2007) under consideration. An initial labor law, effective January 1995 (ended by the end of 2007) contained vague provisions for the protection of workers, but released enterprises from the original restrictions and served to promote business freedom. As a result, the labor market in China is significantly less restrictive than the United States and European economies.[39] Second, the labor market in China is very competitive due to the high volume of labor supply, which favors firms. Third, labor unions in China are very weak, and in most cases they are controlled by firms rather than workers. These factors together result in much lower hiring and firing costs and labor is much more flexible in China than in United States and European countries where labor protection laws, regulations, and unions are much stronger. Even for SOEs, after waves of incremental reforms and restructuring from the late 1970s to the mid-1990s, the responsibility for output decisions was shifted from the state to firms, and firms were allowed to retain more of their profits (e.g., Groves et al., 1994; Li, 1997; Xu, 2011). As a result, the profit objectives of SOEs and non-SOEs have been more aligned than ever. So we assume that the production units of both SOEs and non-SOEs optimally choose labor and material inputs, given their possibly distorted productivity, capital, and input prices.

E Limited Impact of Labor Friction on Our Results

In estimating input prices and productivity, we assume that labor is a flexible input for both SOEs and non-SOEs. Appendix D provided evidence to show that this assumption is reasonable in the context of China during the sample period. However, if this assumption does not hold and labor flexibility in SOEs and non-SOEs changes over time, how would it affect our estimates of input prices and productivity and, more importantly, our regression results regarding the effect of external monitoring? Although we emphasize (in Online Appendix E.4 below) that the timeline of SOE reforms suggests that labor friction is unlikely to drive our main results, we answer the question theoretically and empirically in this appendix. Theoretically, we explicitly show how labor inflexibility/friction may bias our estimates of input prices and productivity. Empirically and more importantly, we show that the impact of this bias is negligible on our main results in the application. Finally, as an alternative method of addressing this issue, we adopt the idea in Hsieh and Song (2015) to use labor share as a proxy for labor friction and control for it in regressions, and we show that our results are robust. .

[39] Using scores of different countries on the Employment Protection legislation indicator developed by the OECD to gauge the strictness of labor laws, Allard and Garot (2010) show that during 1994 to 2007 the labor market in China was fairly deregulated: it was significantly less restrictive than the United State and protective European economies.

E.1 Theoretical Consideration

Using a theoretical model, we explicitly show how labor friction may bias our estimates of input prices and productivity, and more importantly, why the bias can be small in magnitude.

There are different ways to model labor friction. Hsieh and Song (2015) model labor friction as overhead/redundant labor; Berkowitz et al. (2017) model it as an outcome of political pressure (i.e., an objective of SOEs beyond profit). In this subsection, we consider the situation in Hsieh and Song (2015) to demonstrate our key idea, but the result carries over to the case considered by Berkowitz et al. (2017) where SOEs hire more labor because of their objective of labor employment (in addition to the profit objective). Thus, an important implication is that our results from this section can also address the potential issue that SOEs have different objectives or face political pressure compare with non-SOEs.

Specifically, we consider a version of the production function (2) with redundant labor f_{jt}:

$$\tilde{Q}_{jt} = \tilde{\Omega}_{jt} \left[\alpha_L (L_{jt} - f_{jt})^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma} \right]^{\frac{1}{\gamma}}, \tag{38}$$

That is, only $L_{jt} - f_{jt}$ out of total labor L_{jt} is effective in production. f_{jt} represents the redundant workers who produce zero marginal product but cannot be fired because of labor friction. f_{jt} can vary across firms and over time and, for the demonstration purpose, we assume that it is exogenously given for each firm.[40] The redundant workers receive the same wage rate as other workers. The rest of the setup is the same as in Section 3.2.1.

By defining the effective labor as $L_{jt}^* = L_{jt} - f_{jt}$ and substituting it into the production function, we have a similar profit maximization problem as in (7). The firm maximizes its profit by choosing effective labor quantity, the quantity and quality of material inputs, and output:

$$\begin{aligned} \max_{L_{jt}^*, M_{jt}, \tilde{Q}_{jt}, H_{jt}} \quad & P_{jt}\tilde{Q}_{jt} - \tilde{P}_{Mjt} M_{jt} - P_{L_{jt}} L_{jt}^* - P_{L_{jt}} f_{jt}, \\ \text{subject to:} \quad & (1),\ (38) \text{ and } (5). \end{aligned} \tag{39}$$

Compared with (7), the firm's problem is to choose L_{jt}^* (the effective labor) rather than L_{jt} (the total labor). Because f_{jt} is sunk, it does not influence the optimal decision of other variables (i.e., $L_{jt}^*, M_{jt}, \tilde{Q}_{jt}, H_{jt}$). As a result, the first-order conditions are the same as that in our main model, except that they should be evaluated at the effective labor. This is intuitive: with redundant labor

[40] One way to model how f_{jt} can be endogenous chosen is to assume that firms face political pressure to hire excess labor. That is, hiring excess labor is a part of the firm's objective function. This is the case considered by Berkowitz et al. (2017). The predictions in this section carry over to this case.

creating a wedge, the marginal product of labor evaluated at the total labor is no longer equal to the marginal cost of labor (i.e., wage rate) at optimum.

Thus, to make our estimation procedure work, we should evaluate the marginal product of labor at the effective labor (i.e., $L^*_{jt} = L_{jt} - f_{jt}$) in the first-order conditions. Therefore, all the inferred measures carry to the model with redundant labor, with L_{jt} replaced by L^*_{jt}. Here we write these measures (12), (13), (18), and (19) in the Appendix of the paper explicitly to show how they are related to labor:

$$\ln \tilde{P}_{Mjt} = A + (1 - \frac{1}{\gamma}) \ln E_{Mjt} + \frac{1}{\gamma} \ln P_{Ljt} - (1 - \frac{1}{\gamma}) \ln L^*_{jt}, \tag{40}$$

$$\ln \tilde{\Omega}_{jt} = B + [1 - \frac{1}{\gamma}(1 + \frac{1}{\eta})] \ln \left(\frac{E_{Mjt}}{\sigma^*_{Mjt}} \right) + \frac{1}{\gamma}(1 + \frac{1}{\eta}) \ln P_{Ljt} + (1 + \frac{1}{\eta})(\frac{1}{\gamma} - 1) \ln L^*_{jt}, \tag{41}$$

$$p_{Mjt} = C + \frac{1}{\eta\gamma} \ln \left(\frac{E_{Mjt}}{P_{Ljt}} \right) + [1 - \frac{1}{\gamma}(1 + \frac{1}{\eta}) - \frac{1}{\theta}] \ln \sigma^*_{Mjt} + \frac{1}{\eta}(1 - \frac{1}{\gamma}) \ln L^*_{jt}, \tag{42}$$

$$\omega_{jt} = \ln \tilde{\Omega}_{jt} - \frac{1}{\theta} \ln \left[\frac{1}{1 - \sigma^*_{Mjt}} \right], \tag{43}$$

where $A = \frac{1}{\gamma} \ln \left[\frac{\alpha_M}{\alpha_L} \right]$, $B = \ln \frac{\eta}{1+\eta} - \frac{1}{\gamma}(1 + \frac{1}{\eta}) \ln \alpha_L$, $C = \ln \frac{\eta}{1+\eta} + \frac{1}{\eta\gamma} \ln \alpha_L + \frac{1}{\gamma} \ln \alpha_M$, and σ^*_{Mjt} is the output elasticity of material input evaluated at L^*_{jt} and the resulting material quantity.

Ignoring labor friction in the production estimation means using the total labor L_{jt} (and its implied σ_{Mjt}) rather than effective labor L^*_{jt} (and its implied σ^*_{Mjt}) . Intuitively, this overstates the labor input and consequently understates the inferred material quantity input (because of the substitution across inputs). As a result, given the observed material expenditure, this produces an upward bias in the quality-inclusive material price ($\tilde{P}_{Mjt}$). Mathematically, according to (40), this upward bias can be seen from $L^*_{jt} < L_{jt}$ and $0 < \gamma < 1$ (implied by the estimates in Tables OA5 and OA6 of the appendix in the paper). Because material quantity (M_{jt}) is underestimated and so is the output elasticity of material σ_{Mjt} (this is straightforward from the definition of σ_{Mjt} given $\gamma > 0$), the firm capability $\tilde{\Omega}_{jt}$ is overestimated (i.e., using less material but producing the same observed output). This can be seen from (41), given $(1 + \frac{1}{\eta})(\frac{1}{\gamma} - 1) > 0$ and $1 - \frac{1}{\gamma}(1 + \frac{1}{\eta}) > 0$ as implied by the estimates in Tables OA5 and OA6.

The impact on the quality-adjusted input price p_{Mjt} and productivity ω_{jt} is slightly more subtle, but the magnitude of the impact can be small. Intuitively, the inferred p_{Mjt} is the difference between the quality-inclusive material price ($\tilde{P}_{Mjt}$) and material quality. Note that material quality choice depends on productivity ω_{jt} (i.e., (17)), thus it can be partially controlled by $\tilde{\Omega}_{jt}$. Since both $\tilde{P}_{Mjt}$ and $\tilde{\Omega}_{jt}$ are overestimated, their impact on p_{Mjt} offset, leaving the direction of the bias in p_{Mjt} indecisive and small. Mathematically, according to (42), the upward bias force comes from $\frac{1}{\eta}(1 - \frac{1}{\gamma}) \ln(L_{jt})$ because $\frac{1}{\eta}(1 - \frac{1}{\gamma}) > 0$; the downward bias force comes from $[1 - \frac{1}{\gamma}(1 + \frac{1}{\eta}) - \frac{1}{\theta}] \ln(\sigma_{Mjt})$ because

$[1-\frac{1}{\gamma}(1+\frac{1}{\eta})-\frac{1}{\theta}] > 0$ and σ_{Mjt} is underestimated. Thus, p_{Mjt} can be either overestimated or underestimated, depending on which force dominates. Similarly, according to (43), productivity (ω_{jt}) is essentially firm capability $\tilde{\Omega}_{jt}$ after controlling for output elasticity of material (σ_{Mjt}). The overestimated $\tilde{\Omega}_{jt}$ and underestimated σ_{Mjt} (note that $\theta < 0$ in our estimation results) partially offset each other's bias and leave the bias in ω_{jt} indecisive and small.

Of course, the theoretical analysis only considers the bias caused by variables (i.e., using total labor versus effective labor), keeping the parameters of the production and demand functions unchanged. In practice, the parameter estimates will also be biased, and the overall impact is a combination of both. In the following subsection, we show that empirically the overall impact is small and it is unlikely that labor friction is driving our main results in the application.

E.2 Empirical Validation

A direct implication from the above subsection is that differences in labor flexibility between SOEs and non-SOEs may produce gaps in the estimates of input prices and productivity. For this reason, we do not explain the gaps between the two groups of firms as a casual result of monitoring differences. Instead, in the paper, we use variations in the time and spacial dimensions to identify the effect of monitoring. So if the labor friction differences between SOEs and non-SOEs do exist but are unchanged over time, then such differences will be canceled in our Difference-in-Difference design. However, SOEs' labor flexibility may have improved more over time relative to non-SOEs. Even if this is the case, we show in this subsection that ignoring such change has negligible impact on main results in the application.

To see this, we conduct empirical exercises to quantify the sensitivity of our results to labor friction: how different our regression results would be if we observe the amount of redundant labor (and thus effective labor) and take it into account in the estimation. Specifically, suppose the redundant labor of each SOE in the pre-SASAC period is 5% more than that in the post-SASAC period. To take this into account, in our new estimation procedure, we reduce the number of workers (and thus labor expenditure) of each SOE in pre-SASAC periods by 5% (while keeping everything else unchanged) and estimate the entire structural model (to obtain new parameter estimates as well as input price and productivity measures) and the monitoring effect.

Note that the choice of the three levels of redundant labor is reasonable because Hsieh and Song (2015, footnote 20, page 329) point out that *"according to a survey conducted by the Chinese Academy of Social Science in 1995, the narrowly defined redundant workers – that is, those who are idle and have no definite position – accounted for more than 10% of total employment in about half of the state-owned* *firms".* Because the majority cut of redundant labor happened before 2000 in the national movement of layoff redundant SOEs workers, the redundant labor in our data period (especially after 2000) should be much smaller. Moreover, it is unlikely that SOEs completely removed all their labor frictions in a few years after 2003, the actual decline in redundant labor of SOEs should be even smaller. That said, we still experimented with 2.5% and 10% of redundant workers, and the results are similar and are explained as follows.

Table OA2: Exercises: Gauge the Impact of Potential Labor Friction in SOEs

	Difference between SOEs and non-SOEs					
	Before SASAC				Difference: before and after SASAC	
	$\ln \tilde{P}_M$	$\ln \tilde{\Omega}$	p_M	ω	p_M	ω
Data (ignore redundant)	1.320	0.951	0.043	-0.323	-0.076	0.296
2.5% redundant	1.284	0.920	0.047	-0.325	-0.077	0.300
5% redundant	1.251	0.891	0.053	-0.324	-0.078	0.301
10% redundant	1.174	0.825	0.062	-0.323	-0.083	0.306

Table OA3: Results after Accounting for Labor Friction (Redundant Labor)

	2.5% redundant labor		5% redundant labor		10% redundant labor	
	input price	productivity	input price	productivity	input price	productivity
SOE	0.065***	-0.200***	0.067***	-0.205***	0.070***	-0.216***
	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)
SASAC*SOE	-0.021***	0.100***	-0.022***	0.105***	-0.026***	0.115***
	(0.002)	(0.010)	(0.002)	(0.009)	(0.002)	(0.009)
SOE*Dist	0.003***	-0.007***	0.003***	-0.007***	0.003***	-0.006***
	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)
SASAC*SOE*Dist	-0.005***	0.003	-0.005***	0.003	-0.005***	0.003
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
SASAC*Dist	YES	YES	YES	YES	YES	YES
Dist	YES	YES	YES	YES	YES	YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	392900	392900	392900	392900	392900	392900
Adjusted R^2	0.970	0.966	0.970	0.967	0.970	0.966

Standard errors (clustered at the firm level) are in parentheses.

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA2 compares the estimated productivity and input prices in the data (the first row) and those from the hypothetical scenarios with different level of redundant labor in SOEs before SASAC (the last three rows). For each scenario, the differences between SOEs and non-SOEs are reported in terms of mean productivity and input prices. As predicted in Online Appendix E.1 and reported in the first two columns of the table, both of the quality-inclusive input prices and productivity are overestimated if labor friction is ignored. Notably, columns 3 shows that p_{Mjt} is underestimated (but the difference is small), suggesting that the downward bias force dominates slightly; column 4 shows that ω_{jt} from different scenarios are almost the same, meaning that the upward and downward forces of bias almost completely offset. The last two columns of the table shows the "Difference-in-Difference" result: they report the difference of the gaps between SOEs and non-SOEs before and after SASAC. These results imply that the monitoring effect of SASAC in our regressions would be more significant if labor friction is explicitly accounted for.

To verify this is true, in Table OA3, we report the regression results after allowing for different level of labor friction explicitly in our estimation. Each block of the table presents the regression results for the scenario where there is a certain percent of redundant labor and it is taken into account in the estimation. Overall, the results are quantitatively and qualitatively similar to our baseline results of Table 4 in the paper. As expected from the above analysis, the results after controlling for the redundant workers show slightly larger effects of external monitoring, suggesting our baseline results are robust to the potential labor friction issue and the actual external monitoring effect might be larger if labor friction is observed and explicitly accounted for.

E.3 Controlling for Labor Friction using Proxy

An alternative method of addressing the issue is to use proxy to control for the unobserved labor friction. The idea is drawn from Hsieh and Song (2015, Equation 18, page 329): labor friction is positively associated with labor share. Following this idea, we control for labor share in all regressions as a proxy for labor friction. The results, as reported in Table OA4, show that our results are robust.

The aggregate-level analysis in Hsieh and Song (2015) also support that our estimated SASAC effect is not driven by the changes in labor friction. Using the same data, Hsieh and Song (2015, Figure 11, page 330) show that labor friction (including its difference between SOEs and non-SOEs) changed smoothly at the aggregate level. This is in contrast to the sharp improvement of SOEs in term of all three key measure as shown in Figure 5 in our paper. This suggests that our results regarding external monitoring are not simply driven by the change of SOEs' labor friction.

E.4 Arguments from SOE Reform Timeline

As extra arguments, we emphasize that the timeline of SOE reforms suggests that labor friction (i.e., redundant workers) is unlikely to drive our main results. As discussed in Naughton (2006), there was a large wave of layoffs of excess SOE workers in 1990s, with about over 2 million SOE workers being laid off. The peak of the layoff happened during 1998-2000. So the redundant labor is less a problem after

Table OA4: Robustness Check: Control for Labor Friction (using Labor Share)

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.082***	0.066***	-0.268***	-0.216***	-0.182***	-0.143***
	(0.001)	(0.002)	(0.004)	(0.007)	(0.003)	(0.005)
SASAC*SOE	-0.030***	-0.012***	0.071***	0.046***	0.073***	0.025***
	(0.001)	(0.002)	(0.004)	(0.009)	(0.004)	(0.008)
SOE*Dist		0.004***		-0.008***		-0.006***
		(0.000)		(0.002)		(0.001)
SASAC*SOE*Dist		-0.004***		0.002		0.012***
		(0.001)		(0.003)		(0.002)
Labor Friction*SOE	YES	YES	YES	YES	YES	YES
Labor Friction	YES	YES	YES	YES	YES	YES
SASAC*Dist		YES		YES		YES
Dist		YES		YES		YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	873414	392900	873414	392900	873414	392900
Adjusted R^2	0.750	0.779	0.640	0.668	0.327	0.339

Standard errors in parentheses

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

2000. Also, in 1996, over 6000 SOEs went to bankruptcy – this is more than the total number of all bankrupted SOEs in the previous nine years.[41] Surviving SOEs had much improved situation regarding labor flexibility during our data period (1998-2007). Our robust results based on the subsample using the surviving SOEs (i.e., excluding privatized SOEs) support that labor friction is not driving our main results.

F Input Prices Reflected by Material/Labor Expenditure Ratio

Our method of estimation described in Section 3.2.2 is a structural approach to infer key measures from observable data. In particular, input prices (both the quality-inclusive and quality-adjusted measures) are essentially inferred from the ratio of material to labor expenditure (adjusted for wage rate and other variables). In this section, we show how the changes in inferred input prices are associated with the patterns of material and labor expenditure ratio in the raw data. This suggests that although the inferred measures are from a structural model, they are firmly data-based and indeed reflect important patterns of the raw data .

To see this, note that the inferred quality-inclusive input price, (12) in the appendix of the paper,

[41]Source in Chinese: http://news.163.com/special/reviews/reformation01.html

depends on the material to labor expenditure ratio (E_{Mjt}/E_{Ljt}):

$$\ln \tilde{P}_{Mjt} = \frac{1}{\gamma}\ln\left(\frac{\alpha_M}{\alpha_L}\right) + (1-\frac{1}{\gamma})\ln\left(\frac{E_{Mjt}}{E_{Ljt}}\right) + \ln P_{Ljt}, \tag{44}$$

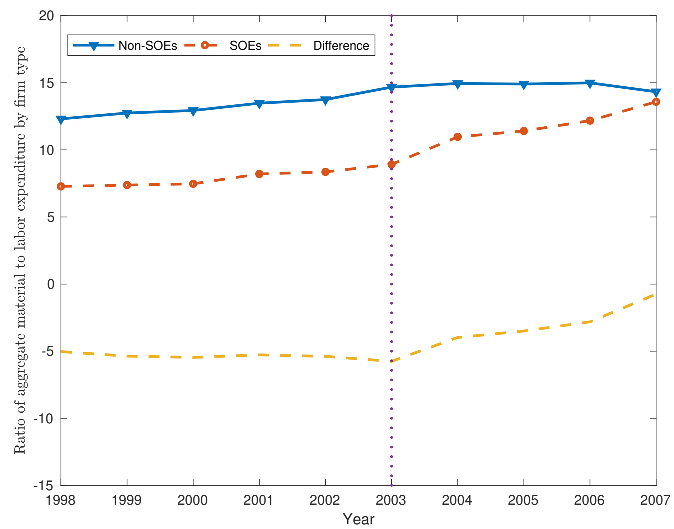
The quality-adjusted input price, (19), also depends on the material to labor expenditure ratio,

$$p_{Mjt} = C + \frac{1}{\eta\gamma}\ln\left(\frac{E_{Mjt}}{E_{Ljt}}\right) + [1-\frac{1}{\gamma}(1+\frac{1}{\eta}) - \frac{1}{\theta}]\ln(\sigma_{Mjt}) + \frac{1}{\eta}\ln(L_{jt}), \tag{45}$$

$$\tag{46}$$

where $C = \ln\frac{\eta}{1+\eta} + \frac{1}{\eta\gamma}\ln\alpha_L + \frac{1}{\gamma}\ln\alpha_M$. Note that our estimated parameters show that $(1-\frac{1}{\gamma}) < 0$ and $\frac{1}{\eta\gamma} < 0$. Hence, an increase in the material to labor expenditure ratio implies a decrease in input prices (conditional on all other variables).

Figure OA1: Material to labor expenditure ratio, by group



In Figure OA1, we show patterns of the aggregate material to labor expenditure ratio for SOEs and non-SOEs. The ratio increases over time for both SOEs and non-SOEs, rationalizing the decreasing input prices in our estimation results. The ratio is lower for SOEs than that of non-SOEs, suggesting SOEs use relatively higher input prices, as we have documented. Importantly, the gap of the ratio significantly shrunk immediately after 2003, which is in sharp contrast to the steady gap before 2003. The majority of the change is due to the rising ratio of SOEs rather than the dropping ratio of non-SOEs. This is consistent with the change of the gap in our estimated input prices (as suggestive evidence of SASAC's impact) in Figure 5 in the paper. Overall, the comparison suggest that the input prices are firmly data-based and indeed reflect important patterns of the raw data, although they are estimated from a structural model.

G Alternative Explanations and Robustness

Although the establishment of SASAC was the main and largest policy shocks regarding SOE during the data period, it was accompanied by several other contemporaneous policy measures which may confound our estimation results. This subsection provides evidence that our results are not driven by these policy measures.

G.1 Privatization and Internal Incentive/Monitoring

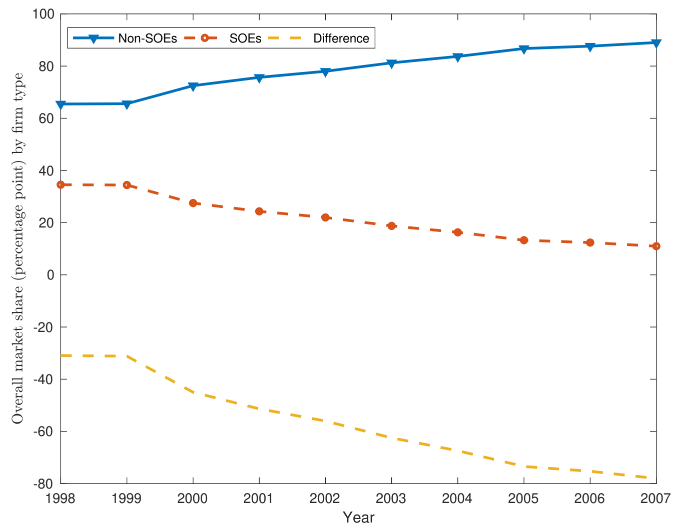
Privatization comes with not only improved monitoring and corporate governance, but also radical changes in many other aspects that potentially have an impact on both productivity and input prices. Given that many firms were privatized during the data period, it is a valid concern that the estimated impact of SASAC might be contaminated or even driven by privatization. In addition, as discussed in Section 2, the central government formed ten guidelines for SOE reform and development in the Fourth Plenary Sessions of 15th Central Committee of the Communist Party in September 1999. These guidelines emphasized the integration of privatization, monitoring, market competition, and establishment of modern enterprise system to improve SOE performance. These policies might have improved the internal monitoring and incentive due to improved corporate governance, contributing to reduced input prices and increased productivity over time.

To rule out this possibility, we drop all observations that involve a change in ownership status during the data period. The remaining sample, as a result, contains all observations that are always SOEs or always non-SOEs from its first to the last year in the sample. Estimation results using this subsample would be free from the privatization concern. We report the results in Table OA7. All the main results are robust. In particular, SOEs still underperform in terms of both input prices and productivity compared with non-SOEs, consistent with the baseline results. SASAC reduces the input prices of SOEs by 4.6% and improves their productivity by 13.9%, relative to non-SOEs. Both estimates are very close to the baseline results in Table 3. The monitoring costs also play a similar role as in the baseline results. These findings confirm that the estimated impact of SASAC on SOEs is unlikely to be driven by privatization.

G.2 Market Power/Competition

The reduction of entry barrier in many industries before 2002 may changed the market power of SOEs, which might well contribute to the change of input prices and (revenue) productivity. If SOEs' market power in the product and input markets increased over time, our estimated SASAC effect could be confounded. To address this issue, we have already controlled for firm size in all baseline regressions. As robustness checks, we carefully secure our results from the potential changes in market power in the following four aspects. First, we show that the results are robust in Table OA8 after controlling

Figure OA2: Overall market shares, by group



for domestic market structure, as captured by the industry-year specific Herfindahl-Hirschman Index (HHI). Second, we include firm-level market share and its interaction with the SOE dummy to capture any potential extra benefits to SOEs (relative to non-SOEs) arising from market power. We also include SOEs' aggregate market share at the industry-city level and its interactions with a SOE dummy in the regressions to capture any potential extra benefits to SOEs (relative to non-SOEs) due to their privileges of being a part of the local SOE cluster. The estimation results in Table OA9 are quantitatively similar to our baseline results. Third, we follow Hsieh and Song (2015) to define non-pillar industries,[42] which are less likely to be associated with "State Capitalism" (i.e., Chinese government sought to maintain the dominance of SOEs). In Table OA11, our main results are robust in the non-pillar industries, suggesting that the monitoring effect is unlikely to be driven by State Capitalism.[43] Finally, in fact, Chinese SOEs faced increasing competition (and thus their market power reduced) over the time period of our consideration in almost all industries. In particular, Hsieh and Song (2015) shows that this is the case even for pillar industries.[44] Consistently, across all industries

[42] Hsieh and Song (2015) (in their Table 6, page 337) define pillar industries as industries of energy (extraction/processing of petroleum, electric and heat power), metal (ferrous and nonferrous), chemical, transport equipment, and communication equipment. Other industries are defined as non-pillar industries.

[43] Interestingly, the interaction term of SASAC, SOE, and local (industry-city) SOE market share is insignificant, further suggesting that there is little "State Capitalism" (working as changing market power) in the non-pillar industries over time.

[44] (Hsieh and Song, 2015, page 336): *"although the goal of the Chinese government was to restrict entry by private firms in the strategic or pillar industries, private firms have actually entered in many of the industries where the state has sought to maintain the dominance of state-owned firms."* They show that although SOEs have a dominant share (measured as value-added share), the state's share has shrunk over 1998-2007 in almost all pillar industries (and the the decline in non-pillar industries is even more dramatic).

under consideration, we show in Figure OA2 that the overall SOE market share decreased from around 35% in 1998 to less than 10% in 2007, while the market share of non-SOEs increased significantly. Importantly, the smooth evolution is in contrast to the sharp change of the estimated input prices and productivity in Figure 5 of the paper. These evidence suggests that changing market power is unlikely to drive our results.

G.3 Restructuring

Chinese SOEs experienced a significant wave of restructuring led by the policy "grasp the large and let go of the small" (Hsieh and Song, 2015). This policy was first formally announced in 1995 at the Fifth Plenum of the Fourteenth Party Congress,[45] with some experiments before that and the first batch of 55 industrial groups being established in 1991. The policy was strengthened in 1997 with another 63 industrial groups being allowed to be established, and further enhanced in 1999 in the Fourth Plenum of the Fifteenth Party Congress. The three years (1997-1999) marked the peak of the reform, with relatively smooth improvement afterwards. The timing and relatively smooth progress after 2000 contrast to the radical improvement of SOE performance in 2004 as shown in Figure 5 of the paper, suggesting that our estimated effect of SASAC is unlikely to be driven by restructuring.

Empirically, because "let go of the small" means to privatize small, less performing SOEs, the result using the subsample that excludes privatized firms in Table OA7 suggests that the monitoring effect is not driven by the effect of "let go of the small". We provide further evidence in the following three aspects to show that "grasp the large" does not drive the monitoring effect either. First, the "grasp the large" policy aimed to restructure 1000 large SOEs into larger industrial groups. Although we do not have the detailed list of restructured firms, we do know the revenue threshold of restructuring firms is 500 million RMB (equivalent to 63 million USD in 2000). We identify 1251 SOEs with revenue over this threshold and drop them in the regressions, and we show that the monitoring effect is robust in Table OA10. Second, restructuring was less likely to happen in non-pillar industries. We follow Hsieh and Song (2015) (in their Table 6, page 337) to define non-pillar industries as industries other than energy (extraction/processing of petroleum, electric and heat power), metal (ferrous and nonferrous), chemical, transport equipment, and communication equipment. We show in Table OA11 that the SASAC effect is significant in non-pillar industries. Third, SOEs that are associated with central, provincial, and city level governments are monitored by SASAC at different tiers, respectively. In Table OA12, we shows that the SASAC has largest effect on city-level SOEs, while the effect is smaller in central and province-level SOEs, which were more likely to undergo restructuring. This result is

[45] Refer to the "Proposals on Formulating the Ninth Five-Year Plan for National Economic and Social Development and the Vision of 2010".

robust after controlling for market share of individual firms as a proxy for market power. This further supports that restructuring ("grasp the large" in particular) is not driving the results of monitoring.

G.4 Change of Privileges

Another possible factor that may drive our result is the privilege of SOEs endowed by the government of China. If the strength of political connections between SOEs and government is increasing over time, then such connections may fortify the privilege of SOEs in input and output markets and enable them to have lower input prices and higher (revenue-based) productivity. If this is true, the result might be contaminated. However, this is unlikely to be the case for several reasons. First, such an increase in privilege, if any, must have happened exactly the same time as the establishment of SASAC (2004 as the cutoff year) to explain the striking jumps presented in Figure 5. This would be a strong coincidence, considering SASAC was designated to enhance the monitoring and supervision of SOEs, which might have decreased (rather than increased) SOEs' privilege. Second, even if there was indeed a sharp increase in SOEs' privilege exactly at the time when SASAC was established, it is more likely the privilege would be given to SOEs closer to the government, which would enlarge the difference between close-by SOEs and remote SOEs after SASAC. Consequently, $\beta_{SASAC*SOE*Dist}$ would be positive for input price and negative for productivity if this is true, which contradicts the findings. Finally, SOEs' privilege may actually have decreased on average over time. For instance, the average of subsidy-to-output ratio decreased from 1.24% (pre-SASAC) to 1.15% (post-SASAC) for SOEs; in contrast, the ratio for non-SOEs increased from 0.28% (pre-SASAC) to 0.31% (post-SASAC). Overall, increased privilege of SOEs, if any, alone cannot explain the patterns we have documented.

G.5 Reduction of Labor Friction

The potentially differential labor friction between SOEs and non-SOEs may produce gaps in their estimated input prices and productivity. For this reason, we do not explain the gaps between the two groups of firms as a casual result of monitoring differences. Instead, we use differences in the time and spacial dimensions to identify the effect of monitoring. If the labor flexibility differences exist but they are unchanged over time, then they will not affect our main results in the application in the Difference-in-Difference design. Thus, the issue boils down to how the potential reduction of SOEs' labor friction (relative to non-SOE) affect our estimates of input prices and productivity and, consequently, our regression results regarding the monitoring effect. We address this issue in four aspects. First, we theoretically show how labor friction could affect our estimates of input prices and productivity. Second and more importantly, we empirically show that the impact caused by ignoring the changes in labor friction is negligible quantitatively in our application. Third, following the idea of Hsieh and Song (2015, Equation 18, page 329), we use labor share as a proxy for labor friction and control for it in all regressions, and our results are robust. Finally, the timeline of SOE reforms also suggests that labor friction is unlikely to drive our main results. Refer to Online Appendix E for more details.

G.6 Potential Differential Pre-trend

To ensure further that the results are not driven by the differential pre-trend (especially for productivity), we design a two-step approach to remove the potential pre-trend and re-estimate the regression specifications. In the first step, we estimate the pre-trend of the dependent variables (input prices, productivity, and TFP) for SOEs and non-SOEs, separately using data in and before 2002, by including a time trend together with firm characteristics and a series of industry and time dummies in each regression. Then we construct the detrended dependent variables by subtracting from the original measures (input prices, productivity, and TFP) their pre-trend estimates *for all years*. Under the assumption that the pre-trend does not change after SASAC, this treatment removes the differential pre-trend between SOEs and non-SOEs. In the second step, we estimate regression specifications using the detrended dependent variables. The estimation results are reported in Table OA13. Again, all the main results are very similar to the baseline results in Tables 3 and 4. In particular, SOEs on average pay 6.9% more for input prices and have 23.1% lower productivity compared with non-SOEs before SASAC. SOEs with higher monitoring costs, as proxied by the distance to their oversight governments, have higher input prices with elasticity 0.003, and lower productivity with elasticity -0.007. The coefficient on the interaction term, $SASAC * SOE * DIST$, is almost the same as that reported in the baseline results as well. The coefficients on $SASAC * SOE$, although quantitatively smaller, are of the same sign and order of magnitude as the baseline results. In total, this suggests that the main results are not driven by the pre-trends of the two firm groups.

G.7 Balanced Panel

A potential concern is that the results might be driven by change in the composition of firms due to entry and exit in the data period. Indeed, entrants and exiters may be different from incumbents in input prices and productivity, and there were substantial entries and exits during the data period.[46] To address this concern, we run the regression specifications using a balanced panel, by dropping all firms

[46]The data set we use surveys private firms with annual sales above five million RMB (about six hundred thousand USD) and all SOEs. We define entrant and exiting as a firm enters or exits the dataset. This definition does not necessarily imply actual entry/exit of firms.

that entered or exited during the data period. The estimation results are reported in Table OA14. In general, the results are consistent with the main results. SOEs pay higher input prices and have lower productivity relative to non-SOEs. Before SASAC, on average SOEs' input prices are 5.4% higher and productivity is 16% lower, both of which are at similar orders of magnitude as that estimated in the main results (i.e., 7.6% and 23.9% respectively) in Table 3. We also find that SASAC reduces the input price and productivity gaps between SOEs and non-SOEs substantially, by 3.0 and 10.8 percentage points, respectively. The results are again very close to the main results (3.9 and 12.6 percentage points, respectively) in Table 3. The impact of monitoring costs on firm performance is similar to the main results as well. Firms with larger external monitoring costs have higher input prices and lower productivity. The establishment of SASAC in general had a larger impact on SOEs with larger oversight distance, consistent with the main results. The results based on the traditional TFP measure are also quantitatively similar to the main results. In sum, these findings suggest that our main results are not driven by the firm entry and exit during the data period.

G.8 World Trade Organization

China joined WTO at the end of 2001. In principle, this might have had an impact on all firms in China—for example, firms were able to access a larger variety of material inputs by importing directly or purchasing from middlemen, and thus input prices could be lowered. In all of the regressions we controlled for year dummies, so the WTO effect (if common to all firms) is controlled in the analysis. Still, it is possible that the WTO membership might have had different impacts on SOEs and non-SOEs. If WTO has a larger impact on SOEs than non-SOEs in productivity and input prices, then the estimated impact of SASAC on SOE performance might be contaminated by the differential WTO effect. To examine this possibility, we estimate an extended specification by adding $WTO_t * SOE_{jt}$ to (22) and (24). If WTO has any heterogeneous impact on SOEs and non-SOEs, this additional term would pick it up. We report the estimation results in Table OA15. All the main results are robust to this additional control. The large gap in input prices and productivity between SOEs and non-SOEs remains, and the magnitude is very close to the baseline results in Tables 3 and 4. The establishment of SASAC improves SOEs' productivity and input prices, relative to non-SOEs. The magnitude of the improvement is also close to the baseline results. In addition, the monitoring costs play a similar role as in the baseline analysis.

As for the WTO effect, we do find that WTO improves the productivity of SOEs more than non-SOEs. An explanation for this effect is the increased competition after WTO, forcing SOEs, which performed worse before WTO, to improve efficiency more. But the impact of WTO on SOEs is much smaller than that of SASAC, by about one-third. Meanwhile, we find a significant but small impact of WTO on SOEs' input prices relative to non-SOEs. Compared with non-SOEs, WTO reduces SOEs' input prices by 1.0% on average, which is less than one-third of the impact of SASAC (3.3%). This small WTO impact again might be driven by the intensified competition following WTO, which forces SOEs to secure lower prices in material procurement but at a very limited magnitude. This finding confirms the result that strengthened external monitoring following SASAC had major impacts on input prices and productivity after 2004.

G.9 Alternative Definition of SOE

In the main results, following Huang et al. (forthcoming) and many others, we define a firm as an SOE if its share of state ownership exceeds 30%. Alternatively, an SOE can be defined based on the firm's registered ownership type. In our main analysis, we choose not to use this way to define SOEs because it is very noisy—some former SOEs do not change their registered ownership type after ownership restructuring. An alternative is to combine the information on state share and registered ownership type. Following Hsieh and Song (2015), we define a firm as an SOE if its state share is over 50% or it is registered as controlled by the state. Hsieh and Song (2015) show that the revenue share and number of SOEs calculated using this definition are very close to those reported in the *China Statistical Yearbook*. We estimate regression specifications using this definition and find that the results are very robust, as reported in Table OA16.

G.10 Transition Period of SASAC

In our analysis, we use 2004 as the cutoff year to define the impact of SASAC: all observations in and after 2004 are considered as being treated by SASAC. However, the establishment of SASAC took some time. Although the central government-level SASAC was established in March 2003, many of its policies and regulations were formed and announced latter in the same year. Meanwhile, province-level SASACs were established during the period between March 2003 and early 2004. Two questions emerge: (1) were firms affected by SASAC in 2003? and (2) were there other factors, such as transition costs that affected firm performance during the transition year (2003)? We check the robustness of our results to these two questions by estimating the regression specifications using a subsample after dropping the observations in the transition year (2003). The results are reported in Table OA17. All the main results of our interest are very close to those in the baseline specification. Quantitatively, the estimates of the impact of SASAC re slightly larger than those in the baseline. For example, after dropping the transition year, SASAC reduces SOEs' input prices by 4.2% and increase productivity by 13.8%. These values are slightly larger than those in the baseline (3.9% and 12.6%). These findings are reasonable, because if SASAC already had some impact during the transition year 2003, then dropping the observations in that year would naturally increase the estimated effect of SASAC.

G.11 Importing and Exporting

As is well-documented in the literature, importing and exporting may have positive impacts on productivity. Grieco et al. (2019) document that importers may have advantages in input prices. If Chinese firms were expanding imports and exports over time, then the estimate of the effect of SASAC would pick up the impact of the increased importing and exporting. To address this potential problem, we further control for lagged import and export dummies in the estimation of (22) and (25), and report the results in Table OA18.[47] We find that all the main parameters of interest are very similar to the baseline results, qualitatively and quantitatively, showing that the results are robust to controlling for importing and exporting.

G.12 Firm Fixed Effects

In the main results, we have controlled for a series of dummies (including province, industry, and year) and firms' registration affiliation type in all the regressions. We think that is enough to control for cross-section fixed effects, because conditional on the same industry, province, year, and registration affiliation type, the unobserved/uncontrolled heterogeneity across individual firms should be small. Given that we further controlled for a set of firm-level characteristics such as firm age, size, and capital intensity, we believe the baseline results are soundly based.

Nonetheless, to ensure further the results are robustness to firm fixed effects, we estimate two fixed effects specifications using data containing all the observations without privatized firms:

$$\begin{aligned} Y_{jt} &= \beta_{soe*SASAC}\left(SOE_{jt} * SASAC_t\right) + \beta_z Z_{jt} + \lambda_f + \lambda_t + \varepsilon_{jt}. \qquad (47) \\ Y_{jt} &= \beta_{soe*SASAC}\left(SOE_{jt} * SASAC_t\right) + \beta_{SASAC*Dist}\left(SASAC_t * *Dist_{jt}\right) \\ &\quad + \beta_{soe*SASAC*Dist}\left(SOE_{jt} * SASAC_t * Dist_{jt}\right) + \beta_z Z_{jt} + \lambda_f + \lambda_t + \varepsilon_{jt}, \qquad (48) \end{aligned}$$

where λ_f captures the firm-level fixed effect. Compared with the main regression in (22), we have dropped the SOE_{jt} term, province fixed effects, industry fixed effects, oversight distance, and the interaction $Dist_{jt} * SOE_{jt}$, because by definition there is no variation in these terms after controlling for firm fixed effects. Moreover, because the full panel dataset is unbalanced, with an average firm

[47] The firm-level trade participation information is from the records of imports and exports from Chinese Customs. We have access to the data from 2000 to 2006 (rather than from 1998 to 2007). As a result, the number of observations is smaller than the previous ones.

tenure of 3.63 years only, the estimates of the fixed-effects model naturally would have a high standard deviation. To avoid this issue, in the regressions we only keep firms that were included in the data for at least five years. This yields a smaller sample of 467,274 observations.

We report the results in Table OA19. In general, the results are consistent with the main results. In all the regressions, we find a negative and significant effect of SASAC on input prices paid by SOEs and a positive and significant effect on productivity, relative to non-SOEs. The quantitative impacts are of similar orders of magnitude compared with the baseline results in Table 3. The role of monitoring costs is also qualitatively similar to our main results in Table 4. Overall, the main results are robust when firm fixed effects are included.

Table OA5: Production Function and Evolution Processes Estimates

Parameter	Agri. Prod.	Food	Textile	Apparel	Leather	Timber	Paper	Printing	Cultural	Chemical
η	-5.894	-6.156	-8.132	-8.888	-8.560	-6.430	-7.922	-7.560	-9.373	-6.684
	(0.034)	(0.064)	(0.050)	(0.089)	(0.112)	(0.065)	(0.089)	(0.106)	(0.176)	(0.039)
σ	1.210	1.440	1.555	1.815	2.382	1.669	1.445	2.643	2.059	1.555
	(0.015)	(0.039)	(0.022)	(0.046)	(0.102)	(0.060)	(0.028)	(0.135)	(0.108)	(0.019)
α_L	0.042	0.076	0.077	0.126	0.100	0.074	0.067	0.122	0.117	0.058
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_M	0.920	0.886	0.892	0.843	0.873	0.900	0.891	0.836	0.853	0.905
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
α_K	0.038	0.038	0.032	0.031	0.027	0.026	0.042	0.042	0.030	0.037
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
$\frac{1}{1-\theta}$	0.167	0.290	0.351	0.430	0.558	0.423	0.294	0.571	0.504	0.342
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
f_0	3.353	1.238	1.434	1.042	0.765	1.676	1.418	0.295	0.823	1.370
	(0.048)	(0.032)	(0.018)	(0.017)	(0.020)	(0.036)	(0.035)	(0.015)	(0.024)	(0.020)
f_{soe}	-0.199	-0.160	-0.069	-0.114	-0.208	-0.090	-0.092	-0.044	-0.102	-0.062
	(0.008)	(0.010)	(0.008)	(0.015)	(0.024)	(0.021)	(0.011)	(0.007)	(0.027)	(0.006)
f_{SASAC}	0.230	0.184	0.177	0.165	0.194	0.332	0.196	0.090	0.152	0.197
	(0.006)	(0.007)	(0.004)	(0.005)	(0.008)	(0.011)	(0.006)	(0.006)	(0.008)	(0.004)
f_1	0.702	0.782	0.656	0.616	0.672	0.555	0.716	0.886	0.647	0.722
	(0.004)	(0.006)	(0.004)	(0.006)	(0.008)	(0.009)	(0.007)	(0.006)	(0.011)	(0.004)
g_0	0.049	-0.038	-0.025	-0.042	-0.059	-0.103	-0.012	-0.038	-0.037	-0.034
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.005)	(0.001)	(0.003)	(0.003)	(0.001)
g_{soe}	0.033	0.027	0.012	0.011	0.021	0.037	0.013	0.014	0.023	0.016
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)
g_{SASAC}	-0.027	-0.019	-0.007	-0.005	-0.012	-0.022	-0.009	-0.009	-0.006	-0.014
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
g_1	0.934	0.955	0.953	0.935	0.940	0.909	0.967	0.973	0.954	0.968
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.005)	(0.002)	(0.002)	(0.004)	(0.001)
#Obs	105955	42308	156914	87878	44174	35809	53812	36528	24505	133420

Table OA6: Production Function Evolution Processes Estimates (continued)

Parameter	Medical	Rubber	Plastic	Machinery	Transp.	Telecom.	Measuring	Waste	Energy
η	-6.020	-7.253	-8.387	-7.449	-8.147	-8.844	-7.966	-7.102	-6.842
	(0.079)	(0.111)	(0.080)	(0.048)	(0.084)	(0.112)	(0.151)	(0.136)	(0.121)
σ	1.280	2.704	1.606	1.990	1.671	1.463	1.405	1.998	2.555
	(0.027)	(0.193)	(0.025)	(0.046)	(0.032)	(0.018)	(0.032)	(0.131)	(0.041)
α_L	0.081	0.088	0.071	0.089	0.093	0.090	0.110	0.086	0.154
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_M	0.860	0.883	0.886	0.880	0.863	0.852	0.832	0.891	0.722
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
α_K	0.058	0.029	0.044	0.031	0.044	0.058	0.058	0.023	0.124
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
$\frac{1}{1-\theta}$	0.208	0.567	0.363	0.484	0.386	0.304	0.280	0.537	0.563
	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.006)	(0.001)
f_0	1.478	0.640	1.222	0.781	0.605	0.747	0.895	1.158	0.192
	(0.041)	(0.025)	(0.022)	(0.013)	(0.015)	(0.019)	(0.030)	(0.047)	(0.009)
f_{soe}	-0.056	-0.064	-0.099	-0.034	-0.027	-0.038	-0.055	-0.122	-0.005
	(0.009)	(0.016)	(0.011)	(0.007)	(0.006)	(0.008)	(0.010)	(0.032)	(0.005)
f_{SASAC}	0.108	0.167	0.186	0.158	0.113	0.158	0.105	0.366	0.030
	(0.007)	(0.008)	(0.005)	(0.004)	(0.005)	(0.005)	(0.007)	(0.021)	(0.005)
f_1	0.792	0.762	0.680	0.743	0.833	0.818	0.793	0.584	0.961
	(0.006)	(0.010)	(0.006)	(0.004)	(0.005)	(0.005)	(0.007)	(0.015)	(0.004)
g_0	-0.021	-0.041	-0.024	-0.044	-0.025	-0.010	-0.014	-0.090	-0.027
	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.009)	(0.003)
g_{soe}	0.016	0.011	0.017	0.019	0.013	0.012	0.011	0.037	-0.005
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)
g_{SASAC}	-0.012	-0.018	-0.010	-0.010	-0.007	-0.007	-0.009	-0.029	-0.006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
g_1	0.951	0.973	0.952	0.970	0.980	0.991	0.958	0.912	0.992
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.008)	(0.002)
#Obs	36614	21574	85589	136895	81922	71614	32750	13051	41107

Table OA7: Robustness Check: Firms with no Privatization

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.102***	0.082***	-0.327***	-0.267***	-0.261***	-0.230***
	(0.001)	(0.002)	(0.005)	(0.009)	(0.004)	(0.007)
SASAC*SOE	-0.046***	-0.022***	0.139***	0.119***	0.115***	0.049***
	(0.001)	(0.003)	(0.006)	(0.012)	(0.005)	(0.010)
SOE*Dist		0.005***		-0.010***		-0.004*
		(0.001)		(0.002)		(0.002)
SASAC*SOE*Dist		-0.006***		0.002		0.019***
		(0.001)		(0.003)		(0.003)
SASAC*Dist		YES		YES		YES
Dist		YES		YES		YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	776413	314870	776413	314870	776413	314870
Adjusted R^2	0.966	0.969	0.966	0.966	0.729	0.707

Standard errors are in parentheses.

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA8: Robustness Check: Control for Competition in Domestic Market

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.076***	0.064***	-0.239***	-0.196***	-0.191***	-0.165***
	(0.001)	(0.001)	(0.003)	(0.007)	(0.003)	(0.005)
SASAC*SOE	-0.039***	-0.019***	0.125***	0.095***	0.094***	0.035***
	(0.001)	(0.002)	(0.004)	(0.010)	(0.004)	(0.008)
SOE*Dist		0.003***		-0.007***		-0.004**
		(0.000)		(0.002)		(0.002)
SASAC*SOE*Dist		-0.005***		0.003		0.015***
		(0.001)		(0.003)		(0.002)
HHI	-0.002***	-0.002***	0.029***	0.020***	0.009***	0.009***
	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
SASAC*Dist		YES		YES		YES
Dist		YES		YES		YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	873367	392854	873367	392854	873367	392854
Adjusted R^2	0.967	0.970	0.966	0.966	0.726	0.708

Standard errors are in parentheses.

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA9: Robustness Check: Control for Market Share

	(1) input price	(2) productivity	(3) TFP	(4) input price	(5) productivity	(6) TFP
SOE	0.067***	-0.230***	-0.175***	0.071***	-0.239***	-0.188***
	(0.002)	(0.007)	(0.006)	(0.002)	(0.007)	(0.006)
SASAC*SOE	-0.010***	0.041***	0.013	-0.011***	0.043***	0.017**
	(0.002)	(0.010)	(0.008)	(0.002)	(0.010)	(0.008)
SOE*Dist	0.003***	-0.007***	-0.004**	0.003***	-0.006***	-0.003**
	(0.000)	(0.002)	(0.002)	(0.000)	(0.002)	(0.002)
SASAC*SOE*Dist	-0.005***	0.003	0.015***	-0.005***	0.003	0.015***
	(0.001)	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)
MktSh * SOE	0.009	0.082	0.028	0.028	-0.004	-0.028
	(0.049)	(0.085)	(0.117)	(0.049)	(0.084)	(0.117)
Local SOE MktSh * SOE				-0.015***	0.032***	0.045***
				(0.001)	(0.006)	(0.005)
Local SOE MktSh				YES	YES	YES
MktSh	YES	YES	YES	YES	YES	YES
SASAC*Dist	YES	YES	YES	YES	YES	YES
Dist	YES	YES	YES	YES	YES	YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	392900	392900	392900	392900	392900	392900
Adjusted R^2	0.768	0.660	0.240	0.768	0.661	0.241

Standard errors in parentheses

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA10: Drop Large (Potentially Restructured) SOEs

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.074***	0.070***	-0.260***	-0.230***	-0.191***	-0.182***
	(0.002)	(0.001)	(0.009)	(0.007)	(0.005)	(0.005)
SASAC*SOE	-0.015***	-0.011***	0.077***	0.043***	0.029***	0.016**
	(0.003)	(0.002)	(0.013)	(0.010)	(0.008)	(0.008)
SOE*Dist	0.004***	0.003***	-0.013***	-0.008***	-0.003*	-0.003*
	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)	(0.002)
SASAC*SOE*Dist	-0.006***	-0.004***	0.007*	0.002	0.013***	0.014***
	(0.001)	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)
SASAC*Dist	YES	YES	YES	YES	YES	YES
Dist	YES	YES	YES	YES	YES	YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity		YES		YES		YES
Observations	533860	386798	533860	386798	533860	386798
Adjusted R^2	0.521	0.736	0.262	0.651	0.135	0.203

Standard errors in parentheses

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA11: SASAC and SOE performance: Non-pillar Industries

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.095***	0.081***	-0.342***	-0.250***	-0.198***	-0.171***
	(0.003)	(0.002)	(0.009)	(0.005)	(0.005)	(0.004)
SASAC*SOE	-0.040***	-0.018***	0.141***	0.037***	0.073***	0.037***
	(0.002)	(0.002)	(0.009)	(0.007)	(0.005)	(0.006)
SASAC*SOE*Local MktSh	-0.001	-0.001	0.007	0.019	-0.009	-0.003
	(0.005)	(0.003)	(0.020)	(0.015)	(0.011)	(0.011)
Local MktSh Interactions	YES	YES	YES	YES	YES	YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity		YES		YES		YES
Observations	880769	268938	880769	268938	880769	268938
Adjusted R^2	0.496	0.733	0.254	0.643	0.142	0.209

Standard errors in parentheses

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA12: SASAC and SOE Performance: Tiered Structure

	(1) input price	(2) productivity	(3) TFP	(4) input price	(5) productivity	(6) TFP
City SOE	0.072***	-0.121**	-0.195***	0.081***	-0.147***	-0.214***
	(0.011)	(0.049)	(0.040)	(0.011)	(0.049)	(0.040)
Provincial SOE	-0.032***	0.031***	0.092***	-0.046***	0.041***	0.122***
	(0.002)	(0.009)	(0.008)	(0.002)	(0.011)	(0.009)
Central SOE	-0.040***	0.113***	0.089***	-0.054***	0.156***	0.127***
	(0.003)	(0.013)	(0.012)	(0.004)	(0.017)	(0.017)
SASAC*City SOE				-0.033***	0.085***	0.073***
				(0.001)	(0.005)	(0.004)
SASAC*Provincial SOE				0.036***	-0.045***	-0.071***
				(0.003)	(0.014)	(0.012)
SASAC*Central SOE				0.032***	-0.105***	-0.077***
				(0.005)	(0.020)	(0.021)
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	873414	873414	873414	873414	873414	873414
Adjusted R^2	0.717	0.630	0.206	0.718	0.630	0.207

Standard errors in parentheses

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA13: Robustness Check: Control for Potential Pre-trend

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.082***	0.069***	-0.275***	-0.231***	-0.205***	-0.179***
	(0.001)	(0.001)	(0.003)	(0.007)	(0.003)	(0.005)
SASAC*SOE	-0.031***	-0.011***	0.072***	0.040***	0.073***	0.013
	(0.001)	(0.002)	(0.004)	(0.010)	(0.004)	(0.008)
SOE*Dist		0.003***		-0.007***		-0.004**
		(0.000)		(0.002)		(0.002)
SASAC*SOE*Dist		-0.005***		0.003		0.015***
		(0.001)		(0.003)		(0.002)
SASAC*Dist		YES		YES		YES
Dist		YES		YES		YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	873414	392900	873414	392900	873414	392900
Adjusted R^2	0.717	0.759	0.629	0.659	0.203	0.223

Standard errors are in parentheses.

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA14: Robustness Check: Balanced Panel

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.054***	0.040***	-0.160***	-0.104***	-0.132***	-0.099***
	(0.002)	(0.003)	(0.008)	(0.014)	(0.006)	(0.010)
SASAC*SOE	-0.030***	-0.015***	0.108***	0.053***	0.090***	0.038***
	(0.002)	(0.004)	(0.008)	(0.017)	(0.007)	(0.013)
SOE*Dist		0.004***		-0.017***		-0.008***
		(0.001)		(0.004)		(0.003)
SASAC*SOE*Dist		-0.004***		0.016***		0.017***
		(0.001)		(0.005)		(0.004)
SASAC*Dist		YES		YES		YES
Dist		YES		YES		YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	133902	84825	133902	84825	133902	84825
Adjusted R^2	0.972	0.974	0.967	0.967	0.810	0.810

Standard errors are in parentheses.

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA15: Robustness Check: Control for WTO Effect

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.080***	0.068***	-0.262***	-0.217***	-0.198***	-0.173***
	(0.001)	(0.002)	(0.004)	(0.007)	(0.003)	(0.005)
SASAC*SOE	-0.033***	-0.012***	0.090***	0.059***	0.084***	0.021**
	(0.001)	(0.002)	(0.005)	(0.010)	(0.004)	(0.008)
SOE*Dist		0.003***		-0.007***		-0.004**
		(0.000)		(0.002)		(0.002)
SASAC*SOE*Dist		-0.005***		0.004		0.016***
		(0.001)		(0.003)		(0.002)
WTO*SOE	-0.010***	-0.011***	0.060***	0.058***	0.018***	0.022***
	(0.001)	(0.001)	(0.004)	(0.004)	(0.003)	(0.004)
SASAC*Dist		YES		YES		YES
Dist		YES		YES		YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	873414	392900	873414	392900	873414	392900
Adjusted R^2	0.967	0.970	0.966	0.966	0.726	0.708

Standard errors are in parentheses.

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA16: Robustness Check: Alternative SOE Defintion by Hsieh and Song (2015)

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.083***	0.068***	-0.270***	-0.216***	-0.212***	-0.179***
	(0.001)	(0.002)	(0.004)	(0.007)	(0.003)	(0.005)
SASAC*SOE	-0.038***	-0.019***	0.123***	0.102***	0.094***	0.035***
	(0.001)	(0.002)	(0.004)	(0.009)	(0.004)	(0.008)
SOE*Dist		0.004***		-0.011***		-0.006***
		(0.000)		(0.002)		(0.002)
SASAC*SOE*Dist		-0.005***		0.002		0.016***
		(0.001)		(0.003)		(0.002)
SASAC*Dist		YES		YES		YES
Dist		YES		YES		YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	873414	392900	873414	392900	873414	392900
Adjusted R^2	0.967	0.970	0.966	0.967	0.727	0.710

Standard errors are in parentheses.

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA17: Robustness Check: Drop Transition Year 2003

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.079***	0.066***	-0.251***	-0.206***	-0.197***	-0.167***
	(0.001)	(0.002)	(0.004)	(0.007)	(0.003)	(0.006)
SASAC*SOE	-0.042***	-0.020***	0.138***	0.106***	0.097***	0.036***
	(0.001)	(0.002)	(0.005)	(0.010)	(0.004)	(0.008)
SOE*Dist		0.004***		-0.007***		-0.005***
		(0.000)		(0.002)		(0.002)
SASAC*SOE*Dist		-0.005***		0.003		0.016***
		(0.001)		(0.003)		(0.002)
SASAC*Dist		YES		YES		YES
Dist		YES		YES		YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	787430	343274	787430	343274	787430	343274
Adjusted R^2	0.967	0.970	0.966	0.966	0.725	0.707

Standard errors are in parentheses.

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA18: Robustness Check: Control for Import and Export

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.073***	0.063***	-0.231***	-0.188***	-0.183***	-0.161***
	(0.001)	(0.002)	(0.004)	(0.007)	(0.003)	(0.006)
SASAC*SOE	-0.031***	-0.013***	0.109***	0.082***	0.073***	0.021**
	(0.001)	(0.002)	(0.004)	(0.010)	(0.004)	(0.009)
SOE*Dist		0.003***		-0.007***		-0.002
		(0.000)		(0.002)		(0.002)
SASAC*SOE*Dist		-0.004***		0.002		0.013***
		(0.001)		(0.003)		(0.002)
SASAC*Dist		YES		YES		YES
Dist		YES		YES		YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Lag IMP & EXP	YES	YES	YES	YES	YES	YES
Observations	649795	301626	649795	301626	649795	301626
Adjusted R^2	0.967	0.970	0.966	0.966	0.725	0.709

Standard errors are in parentheses.

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA19: Robustness Check: Firm Fixed Effects

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SASAC*SOE	-0.020***	-0.007***	0.146***	0.115***	0.055***	-0.006
	(0.001)	(0.002)	(0.005)	(0.011)	(0.006)	(0.011)
SASAC*SOE*Dist		-0.004***		0.001		0.022***
		(0.001)		(0.003)		(0.003)
SASAC*Dist		-0.002***		0.004**		0.004***
		(0.000)		(0.002)		(0.001)
Size	YES	YES	YES	YES	YES	YES
R&D,K-intensity	YES	YES	YES	YES	YES	YES
Observations	467274	216457	467274	216457	467274	216457
Adjusted R^2	0.483	0.451	0.688	0.671	0.042	0.033

Standard errors are in parentheses.

Controled for constant and year fixed effects in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA20: Robustness Check: Further Control for Oversight Distance in the Markov Process of Productivity and Input Prices

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.075***	0.062***	-0.242***	-0.200***	-0.190***	-0.165***
	(0.001)	(0.001)	(0.003)	(0.007)	(0.003)	(0.005)
SASAC*SOE	-0.039***	-0.018***	0.128***	0.097***	0.095***	0.035***
	(0.001)	(0.002)	(0.004)	(0.010)	(0.004)	(0.008)
SOE*Dist		0.003***		-0.007***		-0.004**
		(0.000)		(0.002)		(0.002)
SASAC*SOE*Dist		-0.005***		0.004		0.015***
		(0.001)		(0.003)		(0.002)
SASAC*Dist		YES		YES		YES
Dist		YES		YES		YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	873414	392900	873414	392900	873414	392900
Adjusted R^2	0.967	0.970	0.965	0.966	0.726	0.708

Standard errors in parentheses

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table OA21: Robustness Check: Nonparametric Markov Process of Productivity and Input Prices

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
SOE	0.097***	0.083***	-0.155***	-0.122***	-0.190***	-0.165***
	(0.001)	(0.002)	(0.004)	(0.007)	(0.003)	(0.005)
SASAC*SOE	-0.051***	-0.030***	0.079***	0.055***	0.095***	0.035***
	(0.001)	(0.003)	(0.004)	(0.010)	(0.004)	(0.008)
SOE*Dist		0.003***		-0.004**		-0.004**
		(0.001)		(0.002)		(0.002)
SASAC*SOE*Dist		-0.005***		0.003		0.015***
		(0.001)		(0.003)		(0.002)
SASAC*Dist		YES		YES		YES
Dist		YES		YES		YES
Age, Size	YES	YES	YES	YES	YES	YES
R&D, K-intensity	YES	YES	YES	YES	YES	YES
Observations	873414	392900	873414	392900	873414	392900
Adjusted R^2	0.939	0.940	0.953	0.955	0.726	0.708

Standard errors in parentheses

Added constant and fixed effects of province, year, industry and registration affiliation in all regressions.

* $p < .10$, ** $p < .05$, *** $p < .01$