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

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Abstract

This paper investigates how external monitoring from government influences the performance of state-owned enterprises (SOEs), by affecting managerial expropriation in procurement (proxied by input prices) and shirking in production management (proxied by productivity). We estimate input prices and productivity separately using a structural approach. Empirical application demonstrates strong causal evidence that enhancing monitoring, as an important component of corporate governance, can substantially improve SOEs' input prices and productivity, and higher monitoring costs have negative effects. The negative cost effects are largely alleviated by a monitoring-strengthening policy. The results suggest government monitoring is 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 on firm management — from investors, debtors, or 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 on 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 in analyzing the performance of SOEs has emphasized *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 played by external monitoring from government on SOE performance. As an innovation, 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 by, for example, taking kickbacks, self-dealing, and secret transactions with relational firms. This directly increases the input prices paid by SOEs and consequently reduces profit. 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 profit.

One challenge is that our dataset, like many other production survey datasets, does not include firm-level material 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 of firm performance studies. 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 materials input prices in the estimation of the production function. This approach contrasts to the traditional practice in broad studies of 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]

[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. (2016). In practice, these frameworks assume homogeneous material prices in order 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

Our approach also allows for capital markets distortions/mis-allocations, difference in firm productivity management, and corruptions in input procurement, which is a crucial feature in the performance comparison across firms (especially between SOEs and non-SOEs).

Applying the analysis to the Annual Survey of Industrial Firms in China during 1998-2007, 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 percent lower and they face 6.4 percent 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 to discounted input prices arising from their connections to governments. The higher input prices, as a result, is consistent with the existence of serious corruption and/or shirking in the material procurement process. Because material expenditure accounts for over 80 percent of total variable costs in Chinese manufacturing industries, the impact of such overpayment on materials is substantial: it leads to about a 5.1 percent loss in profits for SOEs.

To explore the causality and circumvent other confounding factors, we use variations of monitoring strength from both time and spatial dimensions to form difference-in-difference analysis and investigate how strengthened external monitoring can have an impact on SOE performance. In the time dimension, 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 the state-owned assets under the leadership of the State Council. It directly enhanced the external monitoring on 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 performance change of these two types of firms. In the data, we observe a quick catch-up of the SOEs' profitability compared with that of non-SOEs after the establishment of SASAC as also 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 reduced the input prices paid by SOEs by 3.9 percent, closing the gap between SOEs and non-SOEs by one-half. It also increased the productivity of SOEs by 12.6 percent relative to their private counterparts, closing the gap by about 53 percent.

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firms (Ornaghi, 2006; Atalay, 2014), and productivity estimation may be biased if the heterogeneity of input prices is correlated with inputs choice and is 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 of corruption that involved government officials and top executives in SOEs from a mainstream media in China, Procuratorial Daily. They found that annual average 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 an enhanced external monitoring and legal punishment strength after 2003.

To strengthen the causality result further, we explore 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 following Huang et al. (forthcoming). 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 to be affiliated with the government, and their distance to their affiliated government can be calculated in the same way. However, the government bears no responsibility to monitor 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.

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 close by. This could arise from the larger potential gains for SOEs farther from their oversight government (i.e., weaker monitoring before SASAC), or that SASAC might have implemented higher order of monitoring on SOEs that were farther away. Both reasons contribute to SASAC's heterogeneous impact of 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 and the direct spherical distance between SOEs and their affiliated governments — affects SOE performance. The 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 relative to non-SOEs. This suggests that the physical interaction of the 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 spacial-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 do 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 aggregate input price by 1.09 percent and reduce the aggregate productivity by 2.61 percent within the group of SOEs. This translates into an increase of input prices by 0.16 percent and a loss of productivity by 0.42 percent for the manufacturing sector. SASAC, as an SOE-exclusive policy, significantly reduced the aggregate input price by 4.03 percent and increased aggregate productivity by 10.97 percent for SOEs relative to non-SOEs. As a result, the aggregate input price for the entire manufacturing sector was reduced by 0.56 percent and aggregate productivity was increased by 1.46 percent.

We conduct a wide range of analysis to secure our results from other potential driving forces, such as privatization, improvement of market competition, and possible enhancement of privilege and internal incentive of 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 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 monitoring from the external 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 also relates 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 perform less 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 behavior 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 estimate 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 both 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-orientated, 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 percent of total assets in manufacturing industries and provided 38 percent of manufacturing employment. Overall, after these reforms, the responsibility for output decisions had been shifted from the state to firms (Xu, 2011), and the profit objective of the SOEs and non-SOEs was more aligned than ever.[3] In particular, SOEs were allowed to retain all their profits starting from 1994 (until 2007), which gave them stronger incentives to maximize profits than before.

Despite the waves of reform, the problem of external monitoring on 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 external monitoring by the government 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. They 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.

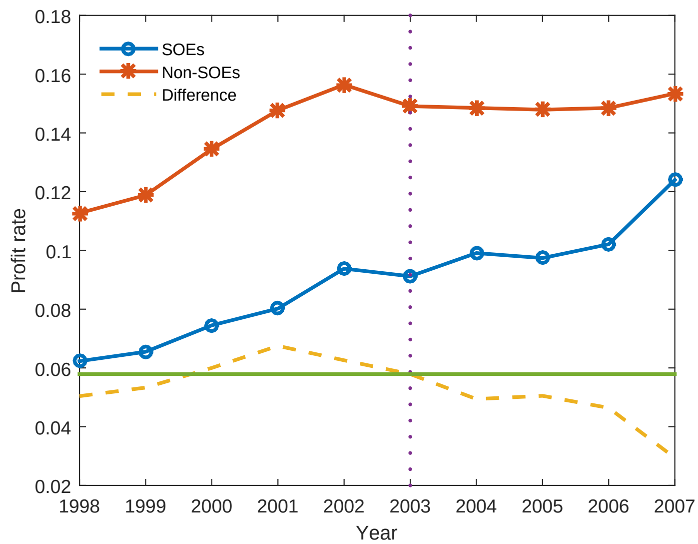
Without effective monitoring, SOE managers almost had ultimate control over the firm's production and transactions. Such a de facto serious insider control problem in corporate governance facilitates managerial expropriation and shirking. First, corruption and kickbacks were common when SOEs purchased 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, SOEs managers may purchase intermediate materials from private firms owned by their family members or close business partners/friends who charge prices 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.[4] These issues drove up the material prices paid by SOEs. Similarly, weak external monitoring on SOEs may cause managerial shirking in production. Overall, these problems echo the SOEs' underperformance in profitability: the average profit rate of SOEs in

[3] Of course, SOEs and non-SOEs might still face different labor market frictions. We discuss its potential impact and the robustness of our results to it in Section 4.3.2.

[4] 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. As a side evidence, take Moutai as an example, 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 percent in 14 months, from November 2012 to January 2014. During the same period, in contrast, the Shanghai Stock Exchange Composite Index remained almost unchanged.

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 the 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 completed 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 powerful government department that takes full responsibility for the performance of SOEs, solving the problem of government shirking of monitoring responsibility before SASAC, when 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 is 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 on SOEs. Second, it helps SOEs to establish a modern enterprise system to improve corporate governance. Third, it is responsible for appointing, evaluating, and removing top executives of SOEs based on their performance. Fourth, it 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 described in Online Appendix A.

These strong monitoring actions yielded fruitful outcomes.[5] During 2004 to 2008, SASAC initiated 77,081 supervision and monitoring projects in SOEs regarding business operation and transactions, which saved over 28 billion RMB (3.5 billion USD) for SOEs, identified 3.69 billion RMB (0.46 billion USD) of corrupt money, and recovered economic losses of over 7.78 billion RMB (0.97 billion USD). 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 (9.5 million USD). 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 on SOEs. Noticeably, Figure 1 shows that the gap of average profit rate between SOEs and non-SOEs was significantly narrowed after SASAC. From 2003 to 2004, the gap reduced by about 1 percentage point (from 6 percent to 5 percent), and it continued to shrink to 3 percent in 2007. The narrowing gap was mainly driven by the improved performance of SOEs after 2003.

For our purpose of 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 actually took the 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 is responsible for auditing and detecting misbehavior and corruption of government officials and SOE managers. It has a

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

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 of SOE managers, and consequently reduced 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 policy initiative regarding SOEs during the data period, it never came alone. First, privatization of SOEs, which started since 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 Sessions of 15th Central Committee of the Communist Party in September 1999, the central government formed ten guidelines for SOE reform and development. The guidelines emphasize the integration of privatization, monitoring, market competition, and establishment of modern enterprise system to improve SOE performance. These policies may improve the internal monitoring and incentive due to improved corporate governance, besides external monitoring. Moreover, Chinese government also gradually reduced the barriers for private firms to enter many industries, including those ones in which SOEs have monopoly power, to meet the WTO requirement and increase the viability of Chinese firms after WTO. Overall, these policies were initiated earlier and they progressed relatively smoothly during the data period, in contrast to the striking improvement of SOE performance 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 is 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 above 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 percent.[6] This definition yields 35,551 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)	1.642	2.143
Material Expenditure (Median)	1.217	1.664
Capital Stock (Median)	1.315	0.439
Wage Expenditure (Median)	0.211	0.145
Material Share over Total Variable Cost (Median)	0.795	0.903
Number of Firms	35,551	290,743

[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 in summary statistics 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.

[6] Alternatively, one could define SOEs 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 Estimating Input Prices and Productivity: An 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.[7] 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 net payment of taking kickback, on which external monitoring can have an impact. A direct conjecture is: 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 resulted productivity measure) is biased if the heterogeneity of unobserved input prices is correlated with inputs choice and is 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 to 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 at period t produces output (Q_{jt}) of quality Φ_{jt}. The output quality depends on the firms' intrinsic ability and their choice of input quality. We assume that goods of higher quality boost demand and so quality-inclusive output is $\tilde{Q}_{jt} = \Phi_{jt} Q_{jt}$.[8] Firms are monopolistically competitive and face a constant elasticity of substitution (CES) demand function:

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

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

[8] 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:

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

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 $\gamma = \frac{\sigma-1}{\sigma}$. 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.[9]

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 follow Grieco et al. (2019) to adopt a functional form that allows productivity and input quality to be either substitutes or complements:[10]

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

The elasticity of substitution between productivity and input quality is measured as $\frac{1}{1-\theta}$: if $\theta < 0$, then productivity and input quality are gross complements of each other. Over time, productivity

[9]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 material may provide more material services, which contributes more to production. In Online Appendix B, we consider an alternative model with both 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, these two models generate the same estimates of the quality-adjusted material prices and productivity, which are our focus.

[10]This paper focuses on material quality as in Kugler and Verhoogen (2012) rather than the quality of capital and labor for three reasons. First, material expenditure share in the total variable cost is much larger (around 85% on average) than the shares of labor and capital, thus material quality potentially has 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, 2004 Chinese Census data shows that 97.7 percent of workers had no college degree and over 82 percent of the firms employed zero college-educated labor in 15 out of the 19 industries under consideration. The share of college employees was also small for the firms who did hire college workers, given the small share of college-educated workers in the total workforce. Also, we use deflated book value of capital as a proxy of capital services following the tradition of the literature, which potentially accounts for the capital quality differences.

$\omega_{jt} \equiv \ln \Omega_{jt}$ evolves according to an AR(1) process:

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

where ϵ^{ω}_{jt+1} 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.[11]

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 follow Grieco et al. (2019) to capture this feature in a simple form:[12]

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

We call $\tilde{P}_{Mjt}$ the quality-inclusive unit prices.[13] We denote $p_{Mjt} = \ln P_{Mjt}$ and assume that it evolves according to an AR(1) process:

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

where ϵ^{p}_{jt+1} 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 on the paper, SOEs, on the one hand, may have privileges over non-SOEs (and thus, face lower input prices) because of their larger bargaining power, connections to the local/central government, and/or access to other SOEs in upstream industries. On the other hand, ineffective external monitoring on

[11] We tested different specifications of the Markov processes of productivity and input prices and found that the results regarding 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; 3) non-parametric 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.

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

[13] $\tilde{P}_{Mjt}$ 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 purchase) 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.

SOE management may increases shirking or even corruption in input procurement, which may increase the input prices SOEs pay. Our methodology of 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 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}) following the methodology developed by Grieco et al. (2016, 2019) 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, following Grieco et al. (2016). 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, following Grieco et al. (2019).

Specifically, the firm's profit maximization problem defined in (7) implies the following first-order conditions (FOC) 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, as in Grieco et al. (2016):

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

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.

As shown in Grieco et al. (2016), the model parameters $\beta \equiv (\alpha_L, \alpha_M, \alpha_K, \eta, \gamma)$ can be identified and estimated by a Nonlinear Linear Least Squares estimator implied by (14) with two additional constraints naturally implied by the model:

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

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 geometric mean of 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 follow Grieco et al. (2019) to use the firm's optimization condition for input quality choice. Specifically, the FOC of endogenous input quality choice is

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

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

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

where $h_{jt} = \ln(H_{jt})$ is the input quality in logarithm and $\sigma_{Mjt} = \frac{\partial F}{\partial M_{jt}} \frac{M_{jt}}{F(\cdot)}$ 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:

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

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

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 Generalized Method of Moments with moment conditions:

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

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 $\epsilon^{p}_{jt+1} = p_{Mjt} - g_0 - g_1 p_{Mjt-1} - g_{soe}SOE_{jt} - g_{SASAC}SASAC_t$. W is a weighting matrix. The set of instrumental variables, 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 total factor productivity measure (TFP) following Levinsohn and Petrin (2003) in order to contrast our study to the traditional analysis of SOEs' productivity. We follow the common practice to use material expenditure deflated by a price index as a proxy of 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.[14] Moreover, it is critical to note that this methodology does allow 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 to access more advanced equipment and technology, which potentially increase their productivity. Meanwhile, they 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 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

[14]See, for example, Katayama et al. (2009); Epple et al. (2010); Gandhi et al. (2016); De Loecker (2011); De Loecker and Warzynski (2012); Zhang (2016); 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 show that our results are robust.

and the bottom panels report the the parameters in (3) and 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 below one when using data from developed countries without controlling for the heterogeneity of input prices. However, this result corroborates 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 Grieco et al. (2016), who use the same method but different data from a Colombian plant-level survey of a variety of industries.

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 firms of different ownership have different evolution processes of productivity and input prices, and the evolution differs before and after SASAC. This finding is captured by the significant coefficients on the SOE and SASAC dummies in both regressions. 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 percent ($e^{0.159} - 1 \approx 0.172$) higher than that paid by the 25th percentile firm.

4 The Effect of External Monitoring

The central question of this paper is: how does external monitoring from government on firm management 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 to 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 vs. Non-SOEs

As discussed in Section 2, Chinese SOEs faced ineffective external monitoring on 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 percent. 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.

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	1196053	873414	1196053	873414	1196053	873414
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.

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

The estimation results confirm the conjecture. SOEs pay input prices that are 6.4 percent 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 of column (2) in Table 2. Because material inputs account for over 80 percent of the total variable cost, the impact of such input price difference is quite significant—it translates to a difference of about 5.1 percent in 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 percent.

Two opposite forces drive the results. On the one hand, SOEs' stronger bargaining power, access to 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), SOEs' TFP is about 16.1 percent 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 does 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 on 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 SASAC and Patterns of Key Measures

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,[15] *direct* cross-sectional comparison among industries is invalid without controlling for industry fixed effects.[16] 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

[15] 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.

[16] 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 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

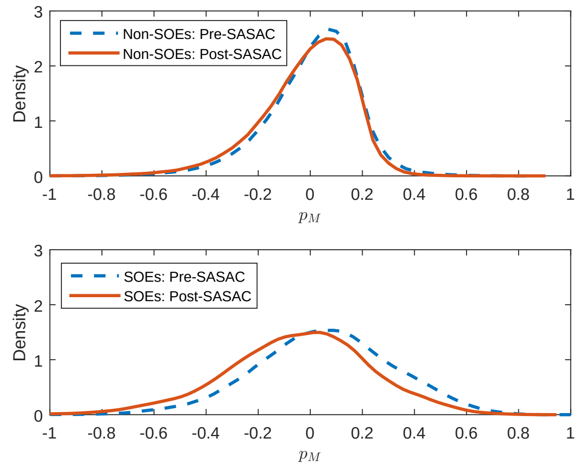


Figure 3: Distributions of ω before and after SASAC, by group

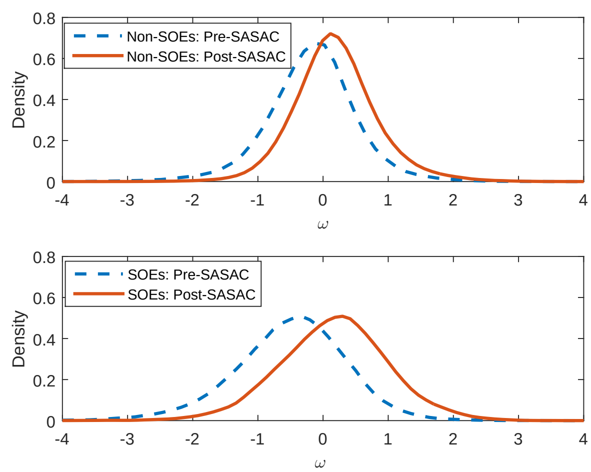
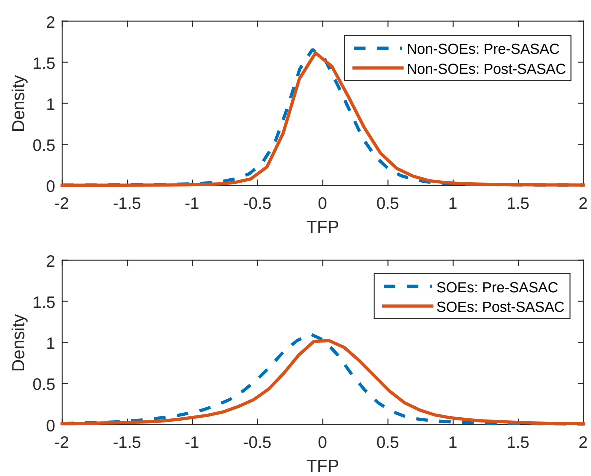
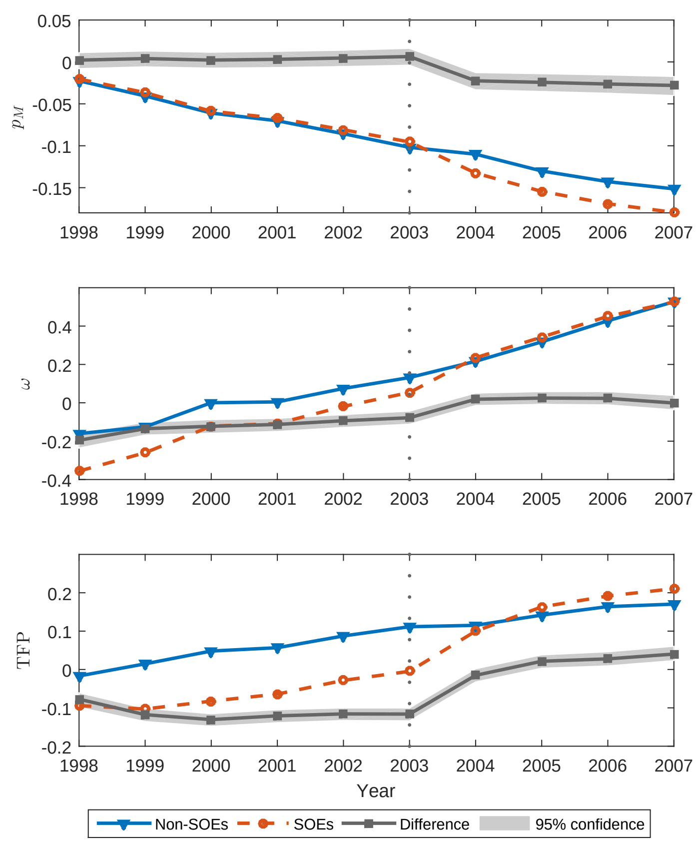


Figure 4: Distributions of TFP before and after SASAC, by group



conjecture that the strengthened external monitoring on SOEs from SASAC (but not on non-SOEs) may have reduced shirking in bargaining for better input prices and/or managerial expropriation in material procurement for 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 of 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 SOEs performance.

Figure 5: Evolution of the means of the key measures, by group



Of course, entry/exit, privatization of SOEs, and different growth trends of SOEs and non-SOEs may also contribute to these patterns. To show that the patterns are robust to these alternative potential drivers, we zoom in our comparison into 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.[17] Although the performance of SOEs was relatively weaker

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

before 2003 in all three measures, the gaps relative to non-SOEs narrowed immediately after the establishment of SASAC and afterwards 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.[18] 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 closing 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-difference analysis in the empirical results.[19]

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

4.2.2 Baseline Estimation Results

To formally investigate 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 afterwards until early 2004, we define the cutoff year for dummy $SASAC_t$ as 2004. That is, $SASAC_t$ equals 1 from 2004 and onward.[20] 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 SOEs definitions, 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

[18] 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.

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

[20] We also conduct 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	1196053	873414	1196053	873414	1196053	873414
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.

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

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

find that SASAC lowers the input prices of SOEs by 3.9 percent on average relative to non-SOEs. As SOEs paid 7.6 percent 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 on 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 suggests 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 percent reduction in input prices roughly contribute 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 reported in columns (3) and (4) after controlling for various firm characteristics. In the full-fledged regression in column (4), SASAC increases the productivity of SOEs by 12.6 percent relative to non-SOEs. Compared with the pre-SASAC productivity difference (23.9 percent) between SOEs and non-SOEs, this impact is large—it reduces the productivity gap by over one-half. This result provides evidence that SASAC may have reduced shirking in production management substantially with 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), SASAC increases SOEs' TFP by 9.5 percent on average, relative to non-SOEs. Meanwhile, the gap between SOEs and non-SOEs before SASAC, is 19.1 percent. 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.[21] In sum, the results show that the strengthened external monitoring on 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 the 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, 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-difference style analysis. For these purpose, 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 added 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-trend between these two groups of firms before SASAC. Specifically, we estimate the following equation:

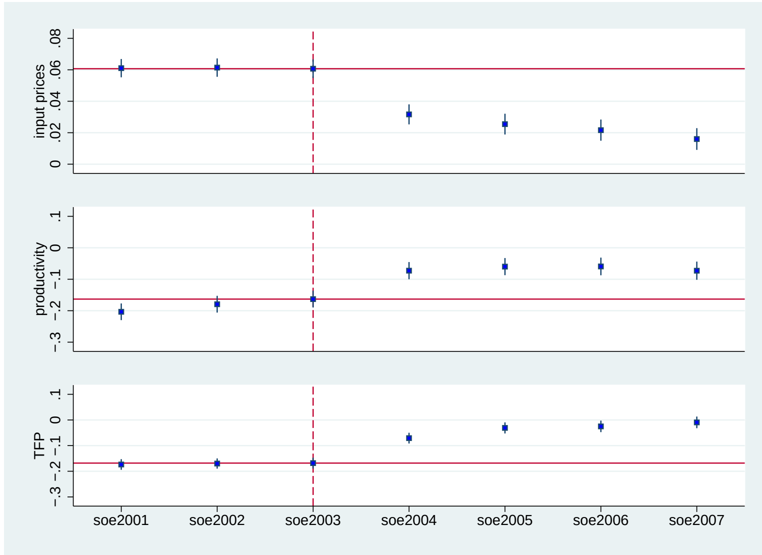
$$Y_{jt} = \beta_0 + \beta_{soe} SOE_{jt} + \sum_{t=2001}^{2007} \beta_{soe*t} \left(SOE_{jt} * D_t \right) + \beta_z Z_{jt} + \lambda_{ind} + \lambda_{prov} + \lambda_t + \varepsilon_{jt}, \tag{23}$$

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 make sure 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 percent confidence intervals.

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 to the differential impact of SASAC on SOEs compared with non-SOEs. In particular, SOE input prices dropped down and productivity jumped significantly after 2003, relative to non-SOEs. TFP estimates show a similar pattern. These results are

[21] 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 facing stronger external monitoring than city-level SOEs, performed better in both 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 higher order of monitoring on them. This result is robust after controlling for market share as a proxy for market power.

Figure 6: Dynamic effect of SASAC and test for pre-trend: β_{soe*t}



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

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 to 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-difference approach is satisfied, at least for the regressions using input prices and TFP. The estimates of β_{soe*t} for productivity, however, do show a slight growing trend before SASAC. From 2001 to 2003, the productivity gap was reduced by about 4 percent in total, with an average annual change of around 2 percent. Nonetheless, this is much smaller than the significant jump in productivity in 2004 (about 9 percent 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.[22]

[22]To ensure further 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.

4.3 The Role of Monitoring Costs: Spatial-dimension Evidence

To further strengthen the causality result between monitoring and SOE performance, we test the impact of monitoring costs on firm performance in the spatial dimension, and examines how the strengthened monitoring from 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 in 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: central, province, or municipality (or prefecture).[23] 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 on SOE's managerial effort from 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

[23] In general, a detailed classification of government levels is: central, province, municipality (or prefecture), county, and township. Nonetheless, the de facto supervision and monitoring on 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.

costs from its effect as 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 both SOEs and non-SOEs similarly are controlled by the distance variable, the monitoring effect is identified by the interaction between SOEs and oversight distance.[24]

Specifically, we estimate the following equation to test 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.[25] We are particularly interested in the parameter $\beta_{soe*dist}$, which captures the impact of monitoring costs on SOEs' performance.

The results are reported in Table 4. Again, SOEs on average pay higher input prices and have lower productivity. But more importantly, we find that monitoring costs (as proxied by oversight distance) matter for SOEs' performance in the preferred input prices and productivity measures. As characterized by the coefficients of $SOE * Dist$, oversight distance increases SOEs' input prices and reduces their productivity. Doubling the oversight distance (in logarithm) increases input prices paid by SOEs by 0.2 percent and reduces SOEs' productivity by 0.6 percent, relative to non-SOEs on average. These findings support the conjecture that higher monitoring costs for distant SOE firms reduces external monitoring on firm management and leads to expropriation and shirking in the production and input procurement processes.

However, column (6) shows that the coefficient of $SOE * Dist$ in the TFP regression is small and insignificant, suggesting that monitoring costs may have ambiguous impact on TFP. A possible cause is that the TFP estimate is biased because of the ignored input price heterogeneity. Another possiblity is that SASAC changed how SOEs of different oversight distance were monitored—thus monitoring costs may affect SOE performance differently before and after SASAC. In addition, our result could be biased if better SOEs are endogenously located nearer (relative to non-SOEs) to the oversight government. That is, the possibility of endogenous oversight distance may confound our estimate of $\beta_{soe*dist}$ as the effect of monitoring costs. Nonetheless, if $\beta_{soe*dist}$ is purely driven by the endogenous oversight

[24] In the data, many of 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.

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

Table 4: Performance Comparison of SOEs and Private Firms: The Role of Monitoring Costs

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
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	541117	392900	541117	392900	541117	392900
Adjusted R^2	0.946	0.970	0.928	0.966	0.669	0.707

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.

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

distance (rather than monitoring costs), then SASAC, as a monitoring-strengthening policy shock, is unlikely to have an impact on $\beta_{soe*dist}$, because for the majority of SOEs the oversight distance did not change over time.[26] These considerations motivate us to investigate if the difference in monitoring costs lead to heterogeneous impact of SASAC in the following subsection.

4.3.2 Monitoring Costs and Heterogeneous Impact of SASAC

The above findings show that higher monitoring costs (as proxied by the greater distance of SOEs to their oversight government) reduce the performance of SASAC. Consistent with Huang et al. (forthcoming), which find that government tends to decentralizes SOEs that are far away, we conjecture that SASAC had the incentive to exert greater level of monitoring strength on SOEs that performed weaker. As a result, the nationwide policy can generate heterogeneous impact: SOEs that were far away from their oversight government improve more in input prices and productivity after SASAC. To examine such a possibility (i.e., impact of SASAC on the monitoring costs), we estimate the following:

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

Compared with (24), there are three new terms in this equation. As usual, $SOE_{jt} * SASAC_t$ captures the impact of SASAC on SOE performance relative to non-SOEs. We use $Dist_{jt} * SASAC_t$ to control for the possibility that factors (such as agglomeration and localized markets) contained in the distance

[26]See Footnote 25 for detailed percentages.

measure may affect firms differently after SASAC. Importantly, $SOE_{jt} * DIST_{jt} * SASAC_t$ is the key term of interest: it captures the impact of SASAC on SOEs of different oversight distances.[27]

The results of the baseline specification are reported in Table 5. The parameter $\beta_{soe*dist}$ has the same sign as that in Table 4, showing that before SASAC the oversight distance is positively associated to the input prices of SOEs and negatively associated to their productivity, relative to non-SOEs. Quantitatively, before SASAC, doubling the oversight distance increases SOEs' input prices by 0.3 percent and reduces productivity by 0.7 percent relative to non-SOEs on average.

More importantly, the estimates of the $\beta_{soe*dist*sasac}$ shows a heterogeneous impact of SASAC on SOEs with different distance 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 it significantly alleviated the negative role of monitoring costs in firm performance. This finding is intuitive. First, SOEs that were far from their oversight government have weaker performance than these 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 higher order of monitoring on SOEs that were far away. Both of these two reasons may contribute to the reduction of the gap between distant SOEs and closer SOEs after SASAC. This also implies that our estimate of $\beta_{soe*dist}$ in Table 4 is not simply driven by the potential endogenous oversight distance.

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 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 labor friction could influence the estimates of input prices and productivity, and we empirically show that the influence is negligible quantitatively 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 from 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

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

Table 5: SASAC and SOE Performance: The Role of Monitoring Costs

	(1) input price	(2) input price	(3) productivity	(4) productivity	(5) TFP	(6) TFP
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	541117	392900	541117	392900	541117	392900
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.

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

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

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, Chinese government might have sought to maintain the dominance and market power of SOEs (usually labelled 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 secure 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 World Trade Organization (WTO) and firms' trade participation.

4.3.3 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 of 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, province 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 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 6, contrasting to the baseline results in Table 5. The SASAC effect on SOEs of different distance still remains robust.

To further explore the mechanism, we examine how travel difficulty between SOEs and their oversight governments influences their performance. We define travel difficulty ("TraDiff") as the ratio of the road distance and the direct (spherical) distance between a firm and its affiliated government. This measure captures the difficulty to travel 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 6. This supports the physical interaction of the government officials with SOEs as a mechanism for distance to matter. In addition, all other coefficients estimates are very close to the baseline results in Table 5. The insignificant effect of SASAC on SOEs of different travel difficulty 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 spacial-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

[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 takes 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.

Table 6: SASAC and SOE Performance: Road Distance and Travel Difficulty

	(1) input price	(2) productivity	(3) TFP	(4) input price	(5) productivity	(6) 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	314665	314665	314665	314530	314530	314530
Adjusted R^2	0.969	0.965	0.705	0.969	0.965	0.705

Standard errors in parentheses

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

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

distance. Specifically, we estimate the following regression model:

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

As shown in the left panel of Table 7, 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 does play a role and that distance-related monitoring costs do influence SOE performance, even after controlling for potentially different effects of spacial-related factors (such as agglomeration) on SOEs and non-SOEs.

[29] In fact, 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 7: The 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	270414	270414	270414	270414	270414	270414
Adjusted R^2	0.970	0.967	0.698	0.970	0.967	0.699

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

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

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

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 7 show that our baseline results are robust: SASAC improves SOEs with higher monitoring costs (which performed worse before SASAC) more in terms of both input prices and productivity.[30]

[30] In fact, 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 condition 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 SASAC effect on distant SOEs. Controlling for this factor correct this bias, resulting in higher SASAC effect on distant SOEs.

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 monitoring resistance created by physical distance.

4.4 Implication on 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 monitoring costs and strengthened SASAC monitoring on the aggregate productivity and input prices, as well as their implication on reducing intermediate input misallocation across firms. Note that because the parameter estimates are based on the Difference-in-Difference analysis, we cannot calculate the overall level effect of external monitoring. Instead, we evaluate the aggregate impact of removing the SASAC effect for SOEs (or the monitoring cost effect) while keeping input prices and productivity of non-SOEs fixed.

First, in the spatial dimension, we have shown that higher monitoring costs due to geographic distance leads to weaker SOE performance by increasing managerial expropriation/shirking. To see its impact at the aggregate level, we consider a counterfactual scenario where the oversight distance (as the proxy for monitoring costs) 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 revenue-weighted aggregate values in the data with the counterparts computed from the counterfactual scenario. The differences as a result capture the aggregate impact of the monitoring costs arising from geographic distance for SOEs relative to non-SOEs. The results are presented in Table 8. The finding reflects that, within the group of SOEs, the monitoring costs increase aggregate input price by 1.09 percent, and reduce aggregate productivity and TFP by 2.61 and 1.46 percent, respectively. As a result, the overall aggregate input price for the entire sector (all firms included) is increased by 0.16 percent, and aggregate productivity and TFP are reduced by 0.42 and 0.22 percent, respectively.[31]

Second, in the time dimension, to understand the aggregate impact of SASAC on SOEs as well as all firms in the manufacturing industries, we consider a counterfactual scenario where the relative effect of SASAC on SOEs compared with non-SOEs is removed. SASAC not only has homogeneous impact on

[31] There are two caveats. First, the analysis assumes that the performance of non-SOEs are unaffected, thus the results only capture the impact on SOEs relative to non-SOEs. Second, 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 percent 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 of weak external monitoring induced by monitoring costs.

Table 8: Impact of Monitoring Costs on Aggregate Input Prices and Productivity (%)

	Input Price	Productivity	TFP
All	0.16	-0.42	-0.22
SOEs	1.09	-2.61	-1.46

Table 9: Impact of SASAC on Aggregate Input Prices and Productivity (%)

	Input Price	Productivity	TFP
All	-0.56	1.46	1.29
SOEs	-4.03	10.97	9.79

all SOEs, but also alleviates the negative effect of monitoring costs. 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 aggregate values with the counterparts from the data. Table 9 shows that, as an SOE-exclusive policy, the relative effect of SASAC on SOEs has significantly reduced the aggregate input price of SOEs by 4.03 percent, and increased aggregate productivity and TFP by 10.97 and 9.79 percent, respectively.[32] Accordingly, the overall aggregate input price of the entire manufacturing sector is reduced by 0.56 percent, and aggregate productivity and TFP are increased by 1.46 and 1.29 percent, respectively.

The above analysis also has important implication on intermediate input misallocation. In principle, the 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 above analysis shows that strengthened external monitoring can improve the input prices of SOEs and reduce the gap by 53 percent, which suggests an improvement in allocative efficiency of intermediate inputs.[33] Comparing to 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 ineffective external monitoring as a source of misallocation in intermediate inputs.

[32]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 percent 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 percent.

[33]This is calculated as 4.03 (impact of SASAC from Table 9) divided by 7.6 (the gap before SASAC from Table 3).

5 Conclusion

Effective external monitoring is an indispensable part of corporate governance to enhance firm performance by reducing shirking and managerial expropriations. This paper empirically investigates how the strengthened external monitoring from 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 percent higher input prices and their productivity is about 20 percent lower, compared with their non-SOE counterparts. We provide evidence on the impact of external monitoring on SOE performance, using variations from both time and spatial dimensions. In the time dimension, the establishment of SASAC, by strengthening monitoring on SOEs exclusively, substantially narrowed the gaps between SOEs and non-SOEs in both 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 the 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 in public policy. The results suggest that enhancement of government monitoring and credible punishment can serve as effective policy instrument 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 can not be privatized due to economic or political reasons.

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