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Slowing Like China: The 2009-2010 fiscal stimulus, and innovation and productivity disparities among POEs and SOEs+

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Abstract

We develop a novel dataset, merging firm-level activity and patenting data with citation information for a large sample of Chinese manufacturing firms. We show that the 2009-2010 fiscal stimulus, which increased subsidies for physical capital investment disproportionately in favor of state-owned firms, did not necessarily slow China's transition from investment-led to innovation-led growth. Quality-adjusted patent applications rose substantially after the stimulus in both SOEs and POEs, while aggregate investment has fallen following a stimulus-induced boom. However, quality-adjusted patenting, R&D, and productivity growth increased in favor of SOEs relative to POEs. We find as much as 90 percent of the SOE-POE quality-adjusted patenting gap is driven by higher SOE skill ratios and subsidies, while financing cost differentials play a smaller role. In the pre-2009 sample, investment subsidies account for 9.3 percent of the observed difference in patent applications; in the post-2009 sample they account for 24 percent. We show that the higher post-2009 SOE-POE productivity growth differential is entirely attributable to the relative increase in subsidies SOEs received; specifically, higher subsidies raised SOEs' productivity growth by increasing their granted patents. We conjecture that reallocation of innovation toward relatively inefficient SOEs has muted the aggregate growth rate relative to that typically attained in an emerging economy's shift from investment-based to innovation-based development. A stylized endogenous growth model with two firm-types differentiated by investment subsidies and investment financing cost rationalizes our empirical findings and implies that the aggregate long-run growth rate in China has been reduced due to the higher investment subsidies awarded to SOEs.

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1. Introduction

In this paper, we explore empirically and theoretically the role of the 2009-2010 fiscal stimulus for the innovation activities and productivity growth of Chinese manufacturing firms. In our empirical work, we find a statistically and economically significant impact of the subsidies the stimulus provided in raising quality-adjusted innovation activity and, through higher innovation activity, productivity growth. We also develop evidence that the subsidies increased the disparity in quality-adjusted innovation and productivity growth in state-owned enterprises (SOEs) relative to privately-owned enterprises (POEs) and crowded-out POE investment. In our data, relatively high SOE quality-adjusted innovation activity has also reduced the POE-SOE productivity level disparity, potentially offsetting the harmful effects of misallocation for aggregate efficiency, however, China's transition from state to market based economy has completely stalled. We conjecture that the subsidy induced reallocation of innovative activity toward relatively low productivity SOEs and away from relatively high productivity POEs has muted the aggregate growth that would otherwise be observed in a developing country's shift from investment-based to innovation-based development. In a stylized endogenous growth model, which can qualitatively reproduce many of our empirical results, we show that, indeed, higher SOE investment subsidies imply lower long-run aggregate productivity growth.

The 2009-2010 stimulus package was intended to offset the impact of the global cyclical downturn but has been widely credited with adverse consequences for China's long-run growth prospects. Bai et al (2015) argue that the easy credit and other financial relief supported a state-owned enterprise investment boom in structures, rather than technology-carrying investments. Large, state-owned infrastructure producers benefited, but the investment boom raised interest rates, crowding out investment by more productive POEs. While Wen and Wu (2014) argue that stimulus packages favoring SOEs successfully stabilize the economy, offsetting their adverse efficiency effects, Zilibotti (2016) views the 2009-2010 stimulus program's favoring of investment by large SOEs as slowing China's transition from investment-led to innovation-led growth. Our analysis implies more complicated effects of the stimulus program for China's transition to innovation-led growth, as well as to a market-based economy.

Figure 1a (right axis) shows systematic slowing of real GDP growth in China since the global financial crisis, and figure 1a (left axis) shows that this has been accompanied by slowing investment growth, growth that had previously propelled China's rapid aggregate real GDP growth. However, figure 1a (left axis) shows that the slowing of investment growth followed a transitory investment boom in 2009-2010 associated with the fiscal stimulus, a boom funded, at least in part, by dramatic growth in bank loans and an increase in government budget contributions to investment funding as figures 1b and 1c illustrate. Figure 1d shows that the debt-ratio of state-owned enterprises (SOEs) has risen significantly since the start of the great recession, in contrast to that of privately owned enterprises (POEs), suggesting the government and loan-funded investment boom of 2009-2010 was biased in favor of SOEs – a fact previously documented by Wen and Wu (2014), Bai et al (2015), and Zilibotti (2016). Moreover, strikingly the first four panels of figure 2 show that since 2009-2010, China's transition from state to privately owned economic activity, explored in detail by Song, Storesletten, and Zilibotti (2011) among others, has completely stalled. Has this stalling of the transition been associated with slower productivity growth? Figure 2e shows two aggregate productivity growth metrics derived by aggregating across the firms in our data; we calculate TFP growth and labor productivity growth. The figure shows that labor productivity growth has plummeted while TFP growth has increased. Neoclassical growth theory implies that the simultaneous observation of increasing TFP growth and declining labor productivity growth reflects faster technological progress and a recession in capital deepening. This feature of the data is at least suggestive of a shift away from investment-led to innovation-led growth. In this paper, we explore explanations for the data in figures 1 through 2 by investigating innovation activity among state-owned and privately owned Chinese firms before and after the 2009-2010 fiscal stimulus.

As long ago as 2006, China's government began to implement a shift from an investment-led growth strategy to an innovation-led growth strategy, making additional subsidies and offering tax benefits for firms that engaged in innovative activities. However, research and development (hereafter, R&D) subsidies and China's economic stimulus plan following the great recession of 2008-2009 disproportionately favored SOEs as Cong, Gao, Ponticelli, and Yang (2019) document. We show that investment subsidies provided through the fiscal stimulus not only increased the number and quality of patent applications, as Wei, Xie, and Zhang (2017) show, but also increased the disparity in innovation activity across state-owned and privately-owned firms. We construct a novel dataset to measure the impact of China's fiscal stimulus for the disparity in innovation quality and productivity between state-owned and privately-owned manufacturing firms, link empirically innovation quality and firm productivity, and discuss the potential effect of the change in innovation quality and productivity disparity for measured aggregate productivity growth.

Specifically, we develop a novel dataset on innovation quality among manufacturing firms in China and use it, together with metrics on firm growth, size, and productivity, to examine empirically the impact of SOE bias in the subsidies awarded as part of the stimulus package. Previous studies of firm-level innovation activity among POEs and SOEs in China have analyzed the quantity of innovation measured by the number of patents a firm applies for but have not adjusted for the quality of innovation. Cao (2020) overcomes this deficiency for POEs, by scraping and merging each Google patent's citation data with patent activity data from China's State Intellectual Office (SIPO) and with privately and state-owned manufacturing firms'

Figure 1a. Investment and GDP growth rates (percent)

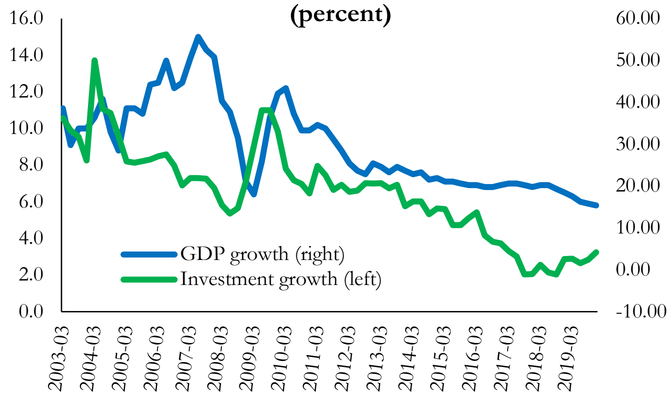
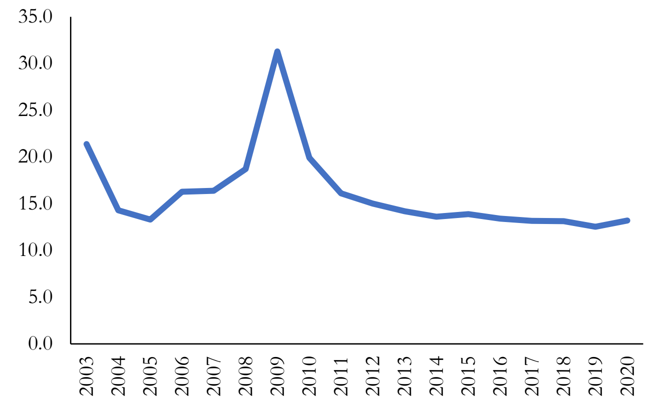


Figure 1b. Bank Loan Growth Rate



Fugure 1c. Share of investment financing from government budget and loans

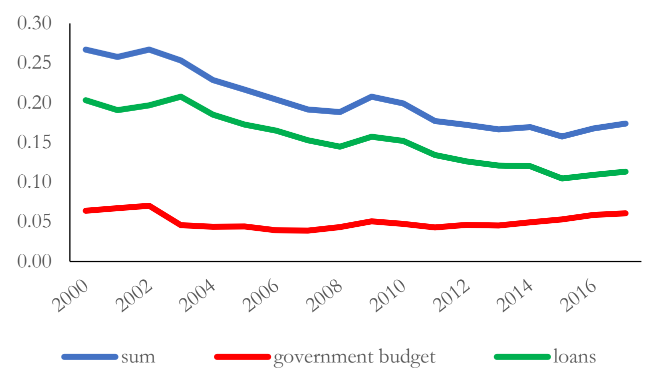
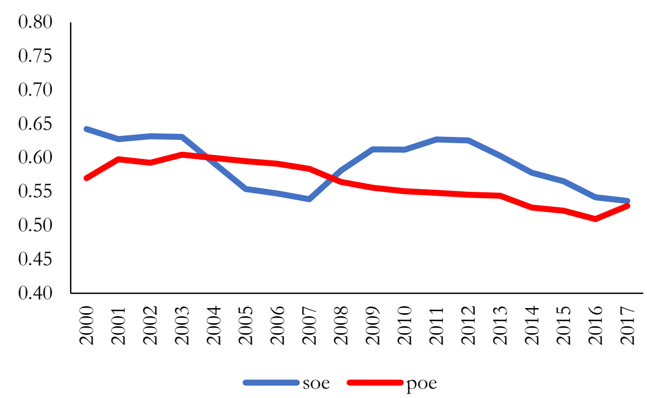


Figure 1d. Debt ratio by firm ownership



Data Sources: Figures 1a: Annual Statistical Yearbook. Figures 1b to 1c: People's Bank of China. Figure 1d: National Bureau of Statistics

operation data from China's Annual Survey of Manufacturing (ASM). We extend Cao's firm-level innovation quality dataset to include SOEs among manufacturing firms in the ASM. We utilize balance sheet information from ASM to measure each firm's physical capital and intangible goods investment, the government subsidies it received, and the interest cost of lending that it confronted. We use the linked Google patent–SIPO dataset to measure the quality of each patent a firm filed in each year.

Consistent with findings in previous literature (see Poncet, Steingress and Hylke Vandenbussche (2010), Guariglia, Liu and Song (2011), and Howell (2016)) we find, first, that POEs receive lower government subsidies and are likely to face higher borrowing costs than SOEs. Furthermore, these differences increased after the 2009-2010 fiscal stimulus. Second, we find that while SOEs quality-adjusted patenting has been higher than that of POEs since 2005, the disparity increased after the policy change in 2009, as did the R&D expenditure disparity in favor of SOEs. Third, we show that SOEs are less productive than POEs in translating R&D expenditures into patent applications, suggesting that the increased innovation disparities we document represent misallocation and are a source of inefficiency. Fourth, we show that the positive SOE-

Figure 2a. Share of number of firms

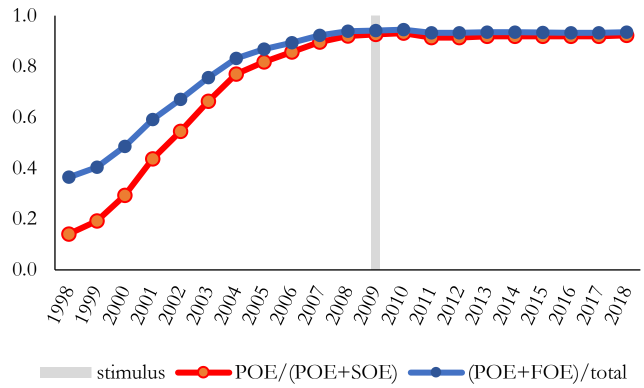


Figure 2b. Share of employment

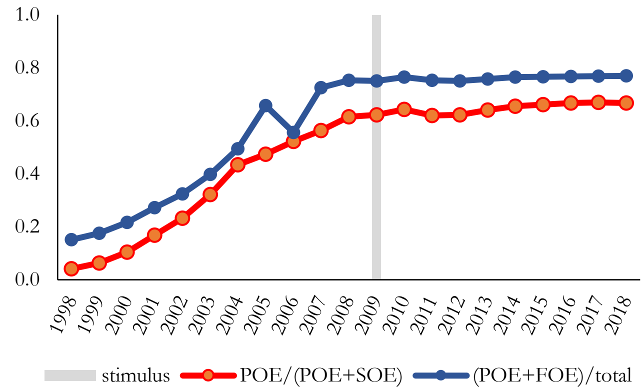


Figure 2c. Share of total assets

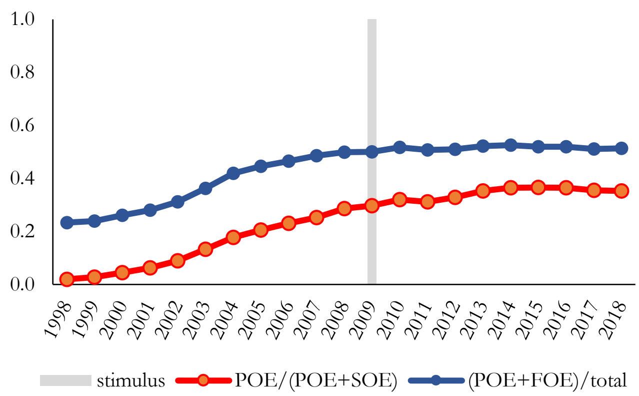


Figure 2d. Share of total liabilities

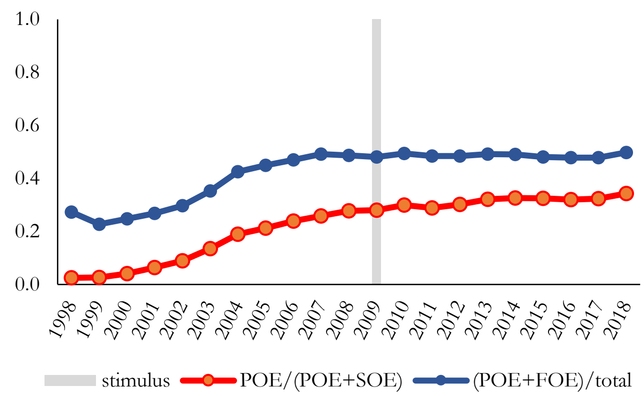
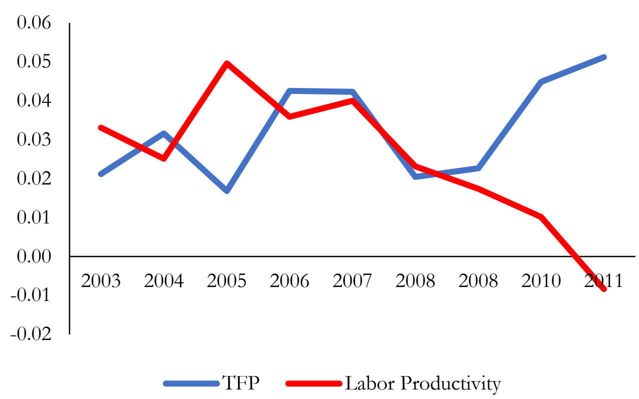


Figure 2e. Aggregate Productivity Growth



Source: Figure 2a to Figure 2b: National Bureau of Statistics, above-scale firms in industry sector. Figure 2e: Annual Survey of Manufacturing firms. authors' calculations. Aggregate productivity, both TFP and labor productivity, is calculated as a value-added weighted sum of firm-level TFP/labor productivity, following Foster, Haltiwanger and Krizan (2001)'s aggregation method. Firm-level TFP is estimated using method proposed by Ackerberg Caves Frazer (2015). Firm-level labor-productivity is calculated as value added over employment, after removing industry and year fixed effect.

POE productivity growth differential increased following the policy change, mitigating the productivity level disadvantage of SOEs. Our data show that China's fiscal stimulus in 2009 and 2010 is associated with an increase in innovation quality disparity between SOEs and POEs and suggest that this may account for a loss of productivity-advantage of POEs relative to SOEs after 2009.

We conduct two mediation analyses to document additional empirical evidence on how state ownership influences firms' innovation activities and productivity growth. We use subsidies and innovation capacities measured by the skill ratios of firms as mediators in the first analysis. We find that the difference in subsidies and skill levels can explain as much as 90% of the observed difference in patent applications between SOEs and POEs. Skill levels contribute the most to the difference in patent application throughout the sample year. The contribution from subsidies increased after the 2009 fiscal stimulus. In the pre-2009 sample, subsidies account for only 9.28% of the observed difference in patent application, however, they account for 23.98% of the difference in the post-2009 sample. In the second mediation analysis, we use granted patents as a mediator to analyze how subsidies and skill levels affect productivity growth. Our empirical evidence is that the only statistically significant impact of subsidies for productivity growth derives from the role of subsidies in increasing a firm's granted patents – its successful innovation activity. We find that 31.4 percent of the increase in productivity growth for SOEs over the sample period can be explained by subsidies through the rise in patents granted to the innovative state-owned manufacturing firms in our sample. We also present evidence which supports local crowding out of private firm investment.

Finally, we develop a stylized endogenous growth model which extends Aghion and Howitt (1998) to allow for two types of firm, SOEs and POEs, differentiated by their access to investment subsidies and by the interest cost they face of funding investments. In the model, physical capital and innovation inputs are complements in producing intermediate goods. In a steady state analysis, we show that increasing SOE investment subsidies in the model replicates qualitatively many of our empirical findings. The model predicts that the long-run aggregate growth rate declines as a result of increased SOE subsidies crowding out POE innovation and investment, despite raising SOE innovation and investment. The key mechanism for this is higher borrowing rates confronted by POEs when SOE investment rises.

Our findings can partially explain the shrinking productivity gap between state-owned and privately-owned firms. Our observation that productivity growth disparity between SOEs and POEs has declined, but associated with exacerbated misallocation is not the first, however. In data prior to the global financial crisis and fiscal stimulus, Hsieh and Song (2015) observed a closing labor productivity gap between SOEs and POEs. This they attributed to policy that favored investment in large, relatively efficient SOEs and eliminated or privatized smaller less efficient firms. Nonetheless, due to capital misallocation in favor of SOEs and away from more efficient POEs, Hsieh and Song (2015) argue that the policy had limited benefits for aggregate growth. Similarly, the reallocation of innovative activity toward less innovation-productive SOEs is likely to have muted the aggregate growth benefits that would otherwise be observed in a developing country's shift from investment-based to innovation-based growth. Nonetheless, our evidence for this is limited. Figure 2e implies that TFP growth among firms in our sample is not a source of slowing real GDP growth, rather, a loss of capital deepening is.

Private firms are believed to be a driving force in China's aggregate productivity growth. Song, Storesletten and Zilibotti (2011) find that about 70 percent of TFP growth in the 1998-2005 period is caused by reallocating resources from inefficient SOEs to more efficient private firms. We conjecture that the reversal of this reallocation after the policy shift in 2009 benefiting state-owned firms may slow China's growth rate by hindering innovation and productivity growth in the private sector. The data in figure 2 clearly show that the transition away from state owned and into privately owned enterprises has ceased since 2009; the model of Song, Storeletten, and Zilibotti (2011) implies that this cessation is attributable to a sufficiently large loss of productivity advantage for POEs. Our data imply that this loss is at least partly attributable to a reallocation of innovation resources in favor of SOEs via the 2009-2010 fiscal stimulus.

Section 2 documents construction of a firm-level innovation quality dataset, measurement of key variables, and descriptive statistics. Section 3 estimates innovation and productivity gaps between SOEs and POEs using panel regression analysis. Section 4 decomposes the sources of innovation and productivity gaps in a mediation analysis. Section 5 presents empirical evidence on local government crowding out of private firm innovation. Section 6 presents a preliminary model, propositions, and proofs. Section 7 concludes.

2. Data

2.1 A firm-level innovation quality dataset

The empirical analysis is based on firm-level operation and innovation activity data from several data sources. The first data source is China's Annual Survey of Manufacturing (ASM). ASM contains balance sheet information for all medium to large manufacturing firms with annual sales greater than 5 million RMB (approximately $800,000). The dataset is cleaned following the method outlined in Brandt, Van Biesebroeck, and Zhang (2014). Specifically, firms that operate for at least three consecutive years and file for a patent at least once during the sample period are retained in the dataset (innovative firms). In addition, only domestic firms are retained; all firms registered as foreign firms or having controlling shareholders that are foreign entities are removed.

We find information on the patents that firms in the sample applied for in China's State Intellectual

Property Office (SIPO) dataset, and from Google Patents. SIPO documents each firm's innovation activities from 1985 to 2016. It contains information on patent applicants, application dates, technology domains of patents, and legal status of patents. ASM and SIPO do not share the same identification numbers for firms, so we link the two datasets by using information on firm names from ASM and the information on patent applicants from SIPO, following the methodology proposed by He, Tong, Zhang, and He (2016). It is well known that patent value varies widely across technology fields, and different patents have diverse impacts on a firm's revenue and productivity growth; for example, Cao (2020) documents and explores these impacts among innovative privately owned Chinese firms. SIPO contains insufficient information on patent citations to accurately measure patent quality and value, however; it does not include forward citation, backward citation, and self-citation distinctions. We therefore supplement the patent data with citation data from Google Patents, which documents when a patent is cited and who cites the patent. Using this information, we condition each patent's citations on technology field, and document the time window in which any citation occurs. We also exclude self-citations, which might bias a patent's quality measure. After these adjustments, we can compare patent quality over time, technology domains, and firm size. We detail our computation of patent quality in the next section.

The matched and cleaned ASM-SIPO sample contains 21,280 medium and large manufacturing firms that patented at least once during the sample period, which we limit to relevant years for which the most complete data is available, from 2003 to 2011. While the sample does not contain all firms in China, excluding producers of services, in particular, it is economically quite large. Total output of firms in the sample averages roughly 22% of GDP during the sample period, and their R&D expenditure averages roughly 32% of China's industrial firm R&D expenditure in 2007. Following Song and Hsieh (2015), state-owned firms are defined as firms either registered as SOEs, or as firms with controlling shareholders that are state (government) entities. We have on average 20% to 34% firms classified as SOEs over the sample period, and 66% to 80% firms classified as POEs (see Table A1 for summary statistics and trends). The percentage of SOEs increases after 2008.

2.2 Variables and measurement

The main variables of interest are firm innovation activities and productivity growth before and after the 2008–2009 fiscal stimulus. Innovation activities are measured by R&D expenditure and patent applications. ASM only reports firm R&D expenditures for the years 2005 to 2007, and 2010. Consequently, we rely mostly on patent applications and patent qualities to measure innovation activity.

Patents are classified into three categories under SIPO: 1) Invention patents which represent "significant progress" over previous technology; 2) utility model patents which represent minor improvements over current products and are insufficiently innovative to be granted invention patent status; and 3) industrial design patents, which like a new marketing strategy target improved consumer aesthetics. In endogenous growth theory, innovations are the main driver of technological progress and productivity growth. However, in the sample, more than 70 percent of industrial design patents concern changes in packaging, labeling, or the design of clothing and furniture, features which do not improve a firm's production process or productivity. We therefore omit industrial design patents from the sample.

Due to the lack of valid citation data, previous work which has studied innovation activities among Chinese firms has focused on innovation frequency measured by patent counts rather than patent qualities. It is well known that a patent's cost and value vary across different technology fields. In addition, patents have diverse impacts on a firm's size and productivity growth. One major innovation might cost more and generate higher future profits and productivity growth than several minor innovations, as Cao (2020) documents. To overcome this, we construct a panel of patent citations for each granted patent using patent forward citation data from Google patent following Cao (2020). We first measure a patent's quality by the number of forward citations it received in a window of five years from its publication date. On average, a patent in the SIPO data receives more than 87 percent of ten-year-forward citations within five years of the patent's publication date. This partly rationalizes our use of the five-year window. However, we also use this window to account for the truncation issue that a more recently published patent has less time to accumulate citations. Next, to make patent quality comparable over technology domains, we compute a patent's relative quality by dividing its citation count by the average citation count for all patents within a 3-digit Industrial Patent Classification (IPC) field. This adjustment removes year and technology field fixed effect in patent citation behavior. We define the relative quality of patent *j* filed by firm *f* at time *t*, as

$$q_{fjt} = \frac{\sum_{\tau=\tilde{t}}^{\tilde{t}+5} citations_{fj\tau}}{\frac{1}{N_t}\sum_{i=1}^{N_t}\sum_{\tau=\tilde{t}}^{\tilde{t}+5} citations_{i\tau}}, \tag{1}$$

where N_t stands for the number of patents filed by Chinese firms in the SIPO office at time *t* and granted within the sample period. Not every innovative firm applies for a patent in every year, so we smooth firm *f's* patent applications, (1), by averaging them in a three-year rolling window:

$$patapp_f = \frac{1}{3}\sum_{j=1}^{N_{ft}}\sum_{\tau=t}^{t+2} q_{fj\tau}\,. \tag{2}$$

In (2), N_{ft} is the total number patent applicants that firm *f* filed in year *t* which are granted within the sample period. Table A2 in the Appendix reports descriptive statistics on firm innovation activities across 2-digit industries.

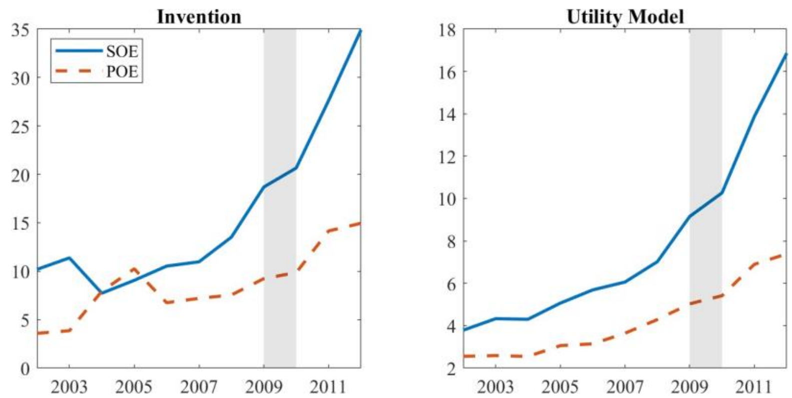
Figure 3a shows time-series of quality-adjusted patent applications by SOEs (blue solid line) and POEs (red dashed line) over the sample period. The y-axis measures the average number of quality adjusted patent applications filed by each patentee, $Patapp_{ft}$. Overall, patent applications grew steadily from 2003 to 2011 in all patent categories. Since 2005, SOEs have systematically filed more invention and utility patents than POEs, and the disparity is rising.

Higher innovation rates of SOEs measured by R&D expenditure rather than by patent applications has been noted elsewhere by Konig et al (2017), with Zilibotti (2016) arguing that state funded and mandated R&D by relatively inefficient SOEs may be viewed as a firm level innovation wedge that reduces aggregate efficiency. R&D expenditure is a noisy measure for innovation in China. Chen et al (2020) find that after the R&D tax policy reform in 2008, 24% of reported R&D expenditure can be accounted by relabeling of non-R&D expenditure as R&D expenditure for tax saving purposes. In addition, it includes expenditures on non-productive industrial designs. Nonetheless, and with these qualifications in mind, in figure 3b we present data on average R&D expenditures in millions of real RMB normalized by firm sales by SOEs and POEs by firm size decile. The data show a large increase in reported R&D expenditures after 2009, by both SOEs and POEs, and a positive R&D disparity in favor of SOEs in both the pre-2009 and post-2009 data that declines only for the very largest firms after 2009. It is worth mentioning that in figure 3b we are restricted by availability of firm R&D expenditures in our data to examining the period 2005 through 2007 in the pre-stimulus period and only 2010 in the post-2009 sample period. Figures 3a and 3b together show rising innovation activity by all firms, and a rising SOE-POE innovation activity disparity. Moreover, the relative rise in SOE quality-adjusted patent applications is likely a result of a relative increase in SOE R&D expenditures, irrespective of noise sources in the R&D data.

In figure 3a, the shaded area is the 2009-2010 period when the Chinese government introduced fiscal stimulus policies that included credit expansion, additional subsidies, and support for firms in high-technology fields and infrastructure. We know that the stimulus policies disproportionately favored SOEs over POEs, and specifically investment by SOEs, as documented by Bai et al. (2015) and Cong, Gao, Ponticelli, and Yang (2019). The data in figures 3a and 3b thus suggest that the fiscal stimulus polices also triggered more rapid growth in innovation activities by SOEs relative to POEs.

Figures 3a and 3b are suggestive of an increase in allocative inefficiency following the fiscal stimulus, due to a rising disparity of SOE relative to POE innovation activity. Furthermore, we do not see in figure 3a

Figure 3a: Quality adjusted innovation in SOEs and POEs



Note: The left panel shows the average number of quality-adjusted patent applications by a patenting firm in the invention category. The right panel shows the average quality-adjusted utility model patent applications filed by patentees. The shaded area, from 2009 to 2010, is the period when the Chinese government initiated fiscal stimulus policies known to favor SOEs.

Figure 3b. R&D investments by SOEs and POEs

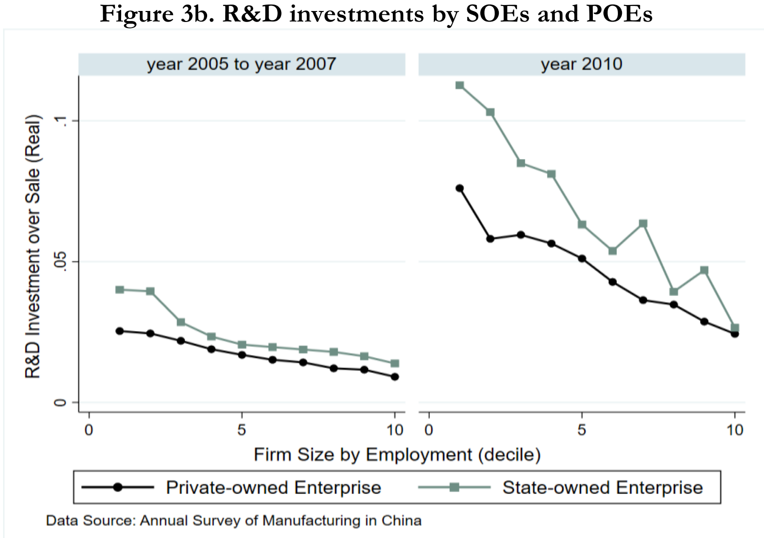
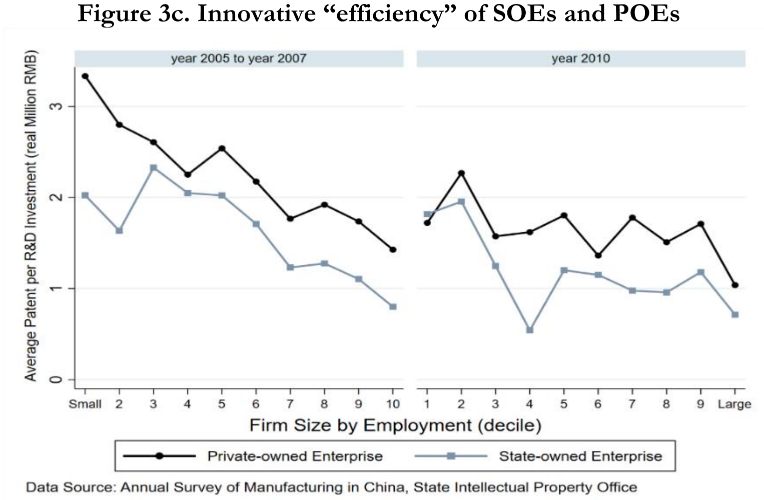


Figure 3c. Innovative "efficiency" of SOEs and POEs



any suggestion that the disparity is declining as time passes since the stimulus. In figure 3c, we present data suggesting that, indeed, there is misallocation of innovation resources in favor of SOEs in that SOEs are less productive in generating patents from R&D expenditure. The figure shows the number of quality-adjusted patents per million real RMB of R&D investment expenditure by firm size decile. These data again are restricted to the pre and post 2009 sub-samples of available R&D expenditures, 2005-2007 and 2010. POEs are more "productive" innovators than SOEs in both sub-samples, although the R&D productivity of both POEs and SOEs declines in 2010 relative to the 2005-2007 period for most firm sizes. We do not see any striking evidence of the argument of Konig et al. (2017), that the degree of inefficiency arising from misallocation of R&D expenditures in favor of SOEs has been declining over time in the form of a decrease in the R&D efficiency advantage of POEs.

Endogenous growth theory implies that an increase in (quality-adjusted) innovation activity, such as that seen in Figures 3a and 3b, increases the rate of technological progress. We evaluate the legitimacy of this in our data using firm-level annual growth in total factor productivity (TFP) to approximate a firm's rate of technological progress. We estimate firm *f*'s TFP using the method proposed by Ackerberg, Caves and Frazer (2015). Specifically, we assume that firm *f* accesses a Cobb-Douglas production function, and estimate it via the following regression equation, using firm-level data on value added, capital, and labor,

$$y_{ft} = \beta_0 + \beta_1 k_{ft} + \beta_2 l_{ft} + z_{ft} + \varepsilon_{ft.} \tag{3}$$

In (3), y_{ft} is the real value added of firm *f* at date *t*, which is calculated as real value of output minus the real value of intermediate inputs plus the real value of value added tax, k_{ft} is the firm's real capital stock, which we construct following Brandt, Van Biesebroeck, and Zhang (2012), l_{ft} is employment in firm *f*, and z_{ft} is the firm's estimated productivity. To better approximate firms' heterogeneity in input choices, we add additional controls as firm's ownership type, industry fixed effects, location, and age in the regression equation.

A firm's innovation activities depend on its financial status and innovation capacity. We use the interest rate on loans received, and subsidies awarded, to approximate a firm's financial status and use a firm's skill ratio and R&D efficiency to approximate innovation capacity. The interest rate on loans confronted by a firm is measured by the ratio of a firm's total interest payments over total debt at each date. Firms facing less severe financial frictions tend to receive lower interest rate loans. In addition, firms with larger government subsidies may be less financially constrained because they have more cash available for investment than those with lower subsidies. However, since larger firms may receive higher subsidies, we normalize each firm's real value of subsidies by dividing them by the real value of its capital stock, k_{ft}. A firm's skill ratio is defined as percentage of employees with first college degrees and above. We calculate a firm's R&D efficiency as

$$RDE_{f,t} = \frac{Patapp_{f,t}}{RD_{ft} + 0.8RD_{f,t-1} + 0.6RD_{t-2}}, \tag{4}$$

where RD_{ft} is the firm's real R&D expenditure at date *t*. Firms with a higher skill ratio or R&D efficiency metric are believed to have higher innovation capacity.

2.3 Summary statistics

Table 1 shows the descriptive statistics for state-owned and privately-owned firm variables before and after the 2009-2010 fiscal stimulus. As data on skill levels is only available for 2004, and data on R&D expenditure is only available for three consecutive years from 2005 to 2007, we present only pre-2009 statistics on these two variables. The growth rate of a firm's TFP is calculated as the change in TFP level which is standardized to remove year effects. External citations per patent is the average number of external citations each patent received within 5 years of patent publication date. Column (1) and (4) list the means of each variable among SOEs, and columns (2) and (5) are the means of each variable among POEs. Columns (3) and (6) list the differences in means between SOEs and POEs.

Table 1. Summary statistics for the merged firm/patent sample

	Pre 2009			Post 2009		
	(1) SOE	(2) POE	(3) diff in mean	(4) SOE	(5) POE	(6) diff in mean
R&D/capital stock	0.0312	0.0134	0.0178*	0.0330	0.0098	0.0232*
	(0.5209)	(0.3179)	(0.0050)	(0.3210)	(0.1596)	(0.0071)
interest fee/total debt	0.0186	0.0320	-0.0134*	0.0179	0.0359	-0.0180*
	(0.0386)	(0.0702)	(0.0004)	(0.0450)	(0.0812)	(0.0007)
subsidies/capital stock	0.0118	0.0115	0.0003	0.0123	0.0054	0.0069*
	(0.0557)	(0.0612)	(0.0004)	(0.0527)	(0.0345)	(0.0007)
external citations/patent	1.2154	1.1758	0.0396*	1.2686	1.1736	0.0950*
	(0.8446)	(0.8692)	(0.0124)	(0.9459)	(0.8196)	(0.0190)
log (TFP)	0.6510	0.7443	-0.1293*	0.9746	0.9274	0.0472*
	(1.0905)	(0.9850)	(0.0084)	(1.1461)	(1.0621)	(0.0174)
TFP growth	0.0108	-0.0032	0.0140*	0.0130	-0.0023	0.0152*
	(0.2230)	(0.2157)	(0.0017)	(0.3201)	(0.3065)	(0.0049)
skill ratio	0.2499	0.1689	0.0810*			
	(0.1812)	(0.1854)	(0.0031)			
R&D efficiency	0.4642	0.4471	0.0171			
	(1.9551)	(1.9748)	(0.0284)			

Notes: Descriptive statistics for the merged AMS-SIPO-Google Patent sample from 2003 to 2011. Foreign owned firms, firms that changed ownership more than twice, and firms that operated less than three consecutive years are excluded. Skill ratio data is only available in 2004. R&D data is only available from 2005 to 2007. See section 2.2 for detail on the construction of each variable. Standard deviations of each variable are in parentheses in columns (1), (2), (4) and (5). The standard deviation for a t-test of difference in means between SOEs and POEs are in parentheses in columns 3 and 6. A * indicates significance of the t-test statistic at 5 percent; a rejection of the null of no difference in means.

Compared to POEs, SOEs make larger R&D expenditures and receive larger subsidies, conditional on size, and face lower external financing costs. The differences between SOEs and POEs in R&D expenditures and financing costs are significant at the 5 percent level and become larger in absolute value and remain significant after 2009. The difference in subsidies received is insignificant prior to 2009, but significant after 2009. Average patent quality, measured by external citations per patent, is also higher in SOEs, and rises after 2009 while that of POEs declines after 2009. The difference between SOE and POE average patent quality in both sub-periods is significant. SOEs' average TFP level is lower than that of POEs before 2009 and higher after 2009, although TFP rises for both types of firm. The SOE-POE negative and positive TFP differential in pre and post 2009 data respectively is significant. Average TFP *growth*, however, is always higher among SOEs and rises in the post-2009 data; the SOE-POE differential is significant in both sub-periods. Finally, the SOE skill ratio and R&D efficiency are both higher than those in POEs in the available pre-2009 data, however, the R&D efficiency difference is insignificant. These data suggest that, on average, SOEs may have better innovation capacity due to the higher human capital of their workers.

As is well-documented in the literature (see Klenow and Hsieh (2009), Brandt, Biesebroeck and Zhang (2012), Hsieh and Song (2015)), we find that state-owned firms are less productive than domestic privately-owned firms. However, our data imply that this productivity gap has been shrinking. This "catch up" effect in productivity is also documented in Hsieh and Song (2015). Some of this catch-up effect might result from China's strategy of privatizing less productive SOEs. In addition, there is evidence that some of the more productive private firms were re-purchased by the government after the stimulus program was instituted, possibly reducing the average productivity of private owned firms in the later years of the sample (Fang, He, and Li (2018)). In our sample, 20 percent of firms switched from state to private ownership, and 9.5 percent of firms switched from private to state ownership during the sample period. To control for these possible effects on the SOE-POE productivity gap, we include in our analysis only firms with constant ownership over the sample period. This implies that our evidence of the shrinking productivity gap may be due to SOEs engaging in more productivity-enhancing innovation activities than POEs. Endogenous growth theory suggests that firms investing in more innovation enjoy higher technology progress, which is measured as productivity growth in this paper.

3. Estimating the SOE-POE innovation gap

To estimate the level difference in innovation activity between SOEs and POEs, we first run panel regressions in which alternative metrics of firm innovation–namely R&D expenditure or quality adjusted patent applications–are regressed on a SOE dummy. The estimated regression equation is:

$$x_{f,j,t} = \beta_0 + \psi_{j,t} + \beta_1 SOE_{f,j,t} + \beta_x' \chi_{f,j,t} + \varepsilon_{f,j,t}, \tag{5}$$

where $x_{f,j,t}$ denotes the R&D expenditure to capital ratio or the quality adjusted patent applications to capital ratio (in equation (2)) of firm f in industry j at time t. $SOE_{f,j,t}$ is a dummy variable which equals 1 if firm f in industry j is classified as a state-owned enterprise at time t, and $\psi_{j,t}$ are industry-year-location fixed effects. Finally, $\chi_{f,j,t}$ is a vector of additional control variables including a firm's capital intensity, firm size measured by the log of employment, and firm age. Then, β_1 reflects the innovation "premium" for SOEs. Standard errors are clustered at the year-industry-location level to absorb any unobserved drivers that are common across firms within locations and sectors within a year.

We run this panel regression in two periods: for 2003 through 2008, prior to implementation of the 2009 fiscal stimulus, and for the years 2009 to 2011–years during and following the stimulus. Columns (1) and (5) in table 2 document the results. Panel A presents the regression results in which quality adjusted patents are the dependent variable, and panel B presents regression results in which R&D expenditure to capital is the dependent variable. Column 1 in panel B shows that before 2009, SOEs tended to invest more in R&D than POEs, however, the SOE-POE differential in quality-adjusted patent applications shown in panel A is not significant. This is an important distinction, potentially, if R&D expenditure measures innovation effort and quality adjust patents measure innovation success; prior to the fiscal stimulus, while SOEs expended more R&D effort than POEs they did not achieve significantly higher innovation success rates. By contrast, from 2009 through 2011, the SOE-POE differentials in both R&D investment and quality-adjusted patent applications become significant and both are also larger positive values. The SOE-POE differential in quality adjusted patent applications is especially large in the post-stimulus sample period.

To further evaluate the size and significance of SOE-POE differentials in quality-adjusted patenting and size-adjusted R&D investment, we include extra control variables which, in theory, may also contribute to a firm's patent applications and R&D investments. Based on the extant literature on firm innovation,[1] firms receiving government support, firms with higher innovation capacity, and firms facing lower financing cost tend to innovate more than those receiving less government support, with lower innovation capacity, or facing higher financing cost. We use received subsidies to measure government support, the skill ratio to proxy innovation capacity, and the interest payments to total debt ratio to proxy for financing costs, as we did in the descriptive statistics in table 1. We then run the following set of amended panel regressions:

$$x_{f,j,t} = \beta_0 + \psi_{j,t} + \tilde{\beta}_1 SOE_{f,j,t} + \beta_2 sub_{f,j,t-1} + \beta_x' \chi_{f,j,t} + \varepsilon_{f,j,t}, \tag{6}$$

[1] See, for example, Acemoglu, Akcigit, Alp, Bloom, and Kerr (2019) and Hall and Lerner (2010) on innovation capacity, and Brown, Fazzari and Peterson (2009) and Brown, Martinsson and Petersen (2013) concerning the role of financing cost.

$$x_{f,j,t} = \beta_0 + \psi_{j,t} + \hat{\beta}_1 SOE_{f,j,t} + \beta_2 sub_{f,j,t-1} + \beta_3 SR_{f,j} + \beta_x' \chi_{f,j,t} + \varepsilon_{f,j,t},$$
$$x_{f,j,t} = \beta_0 + \psi_{j,t} + \breve{\beta}_1 SOE_{f,j,t} + \beta_2 sub_{f,j,t-1} + \beta_3 SR_{f,j} + \beta_4 INT_{f,j,t} + \beta_x' \chi_{f,j,t} + \varepsilon_{f,j,t}.$$

In (6), $sub_{f,j,t-1}$ are subsidies received at *t-1*, and $SR_{f,j}$ is the lone 2004 observation on a firm's skill ratio which may be viewed as a firm fixed-effect. The coefficient $\tilde{\beta}_1$ reflects the SOE innovation premium after controlling for subsidies received in the prior period, and the difference between $\tilde{\beta}_1$ and β_1 reflects the subsidy premium–how much of the difference in the dependent variable innovation measure (patent applications or R&D expenditure) between SOEs and POEs can be accounted for on average by different levels of subsidies received. Similarly, the difference between $\hat{\beta}_1$ and $\tilde{\beta}_1$ documents any SOE-POE skill premium, and the difference between $\breve{\beta}_1$ and $\hat{\beta}_1$ any cheap financing premium of SOEs relative to POEs. In table 2, columns (2) to (4) and columns (6) to (8) present the regression results.

As expected, subsidies and the skill ratio are strongly positively, and significantly, associated with a firm's innovation activity measured by patent applications and R&D investment in all three specifications of the amended regression model in equations (6). This is true both before and after the fiscal stimulus. Notably, subsidies and the skill ratio have larger positive effects for quality-adjusted patenting after the fiscal stimulus than prior to it, but somewhat smaller positive effects for R&D expenditures. The impact of interest cost on innovation activity is ambiguous. The interest fees to total debt ratio is *positively* associated with quality adjusted patent applications before 2009, while its effects for R&D investment during both sub-sample periods are insignificantly different from zero. Interest cost is, however, negatively associated with quality-adjusted patenting *after* 2009 as one would anticipate; in theory, higher interest costs imply tighter financial constraints limiting the funding of innovative activities. One obvious potential explanation for the positive patenting effect prior to 2009 is that the interest fee to total debt ratio mismeasures a firm's financing cost. For example, the total debt is measured at its fiscal year-end value, whereas interest payments are made by a firm throughout the year. It is possible that financially strong firms can repay debt before fiscal year-end. Using the year-end value of total debt might underestimate the actual amount of debt a firm has during that year, and thus overestimate the financing cost for financially strong firms that repay debt within the current fiscal year. If financially robust firms conduct more successful innovative activity reflected in patenting, that would result in a positive relation between patenting and the interest rate to total debt ratio.

Looking at the first row of panels A and B, columns 1 to 3 and columns 5 to 7 show that the estimated impact of state ownership on quality adjusted patenting and R&D investment is reduced when we condition on the subsidies a firm receives, and when we condition on both the subsidies it receives and the

Table 2. Estimated innovation differentials between SOEs and POEs

	Pre 2009				Post 2009			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Dependent variable quality adjusted applications for invention and utility model patents to capital stock ratio								
SOE	0.0278	0.0145	-0.0467***	-0.0449***	0.0830***	0.0737***	0.0102	0.0044
	(0.0174)	(0.0184)	(0.0178)	(0.0178)	(0.0312)	(0.0347)	(0.0343)	(0.0348)
log $(\text{subsidies})_{t-1}$		0.0679***	0.0522***	0.0523***		0.1085***	0.0925***	0.0928***
		(0.0077)	(0.0068)	(0.0068)		(0.0100)	(0.0098)	(0.0098)
skill ratio			1.1037***	1.1025***			1.1891***	1.1914***
			(0.0439)	(0.0439)			(0.0699)	(0.0700)
interest fees/debt				0.0116***				-0.2139**
				(0.0039)				(0.0917)
N. Observations	106,961	94,800	94,798	94,356	39,021	30,727	30,727	30,335
R-Sqaured	0.2177	0.2242	0.2501	0.2507	0.1874	0.2026	0.2233	0.2239
Panel B. Dependent variable R&D expenditure to capital stock ratio								
SOE	0.0332***	0.0300***	0.0113	0.0117	0.0357***	0.0202***	0.0013	0.0023
	(0.0106)	(0.0102)	(0.0107)	(0.0107)	(0.0106)	(0.0088)	(0.0111)	(0.0109)
log $(\text{subsidies})_{t-1}$		0.0213***	0.0159***	0.0159***		0.0143***	0.0101***	0.0103***
		(0.0034)	(0.0027)	(0.0027)		(0.0038)	(0.0030)	(0.0031)
skill ratio			0.3204***	0.3215***			0.2213***	0.2229***
			(0.0457)	(0.0457)			(0.0589)	(0.0591)
interest fees/total debt				0.0792				0.0922
				(0.0767)				(0.0689)
N. Observations	56,541	53,307	53,307	53,300	13,172	10,667	10,667	10,666
R-Squared	0.0600	0.0632	0.0807	0.0808	0.0469	0.0425	0.0595	0.0597

Notes: R&D investment data are only available in 2010 and from 2005 to 2007. In each regression, capital intensity, firm age, firm size measured by the log of employment, and industry-year-location fixed effects are included but not reported. The pre-sample mean of patent applications is controlled in regressions in the panel A. Robust standard errors clustered at year-location-industry level are reported in parentheses. $***$, $**$ and $*$ indicate significant level at 1%, 5% and 10%, respectively.

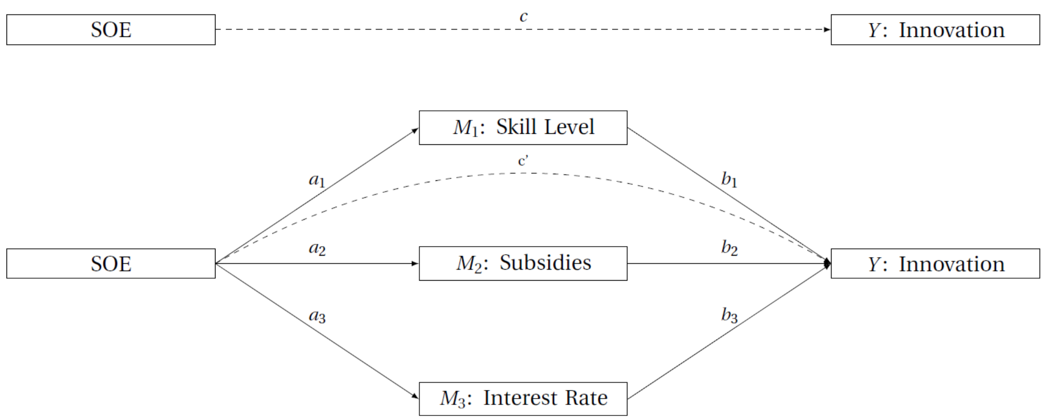
firm's skill ratio. This, again, is true both in the pre-2009 and post-2009 sample periods. In addition, once we condition on both subsidies *and* the skill ratio, the (smaller) positive SOE-POE R&D differential becomes statistically insignificantly from zero in both sample periods, and in the post-2009 sample the (smaller) positive SOE-POE quality-adjusted patenting differential also becomes statistically insignificant. However, once we condition on both subsidies and the firm's skill ratio, in the *pre*-2009 sample the SOE-POE quality-adjusted patenting differential becomes negative; before 2009, SOEs tended to innovate through quality-adjusted patenting significantly *less* than POEs after controlling for skill levels as well as subsidies. The pre-stimulus negative SOE-POE quality-adjusted patenting differential survives the addition of the interest-cost variable in column 4 of panel A. However, the negative SOE-POE patenting differential disappears in the post-stimulus sample period, as shown in columns 7 and 8 irrespective of the large SOE-POE skill ratio differential that we observed in table 1. What the negative pre-stimulus differential means is that the pre-fiscal stimulus positive SOE-POE differential in innovation we observe in figure 3 is mainly driven by different skill levels in the two sectors. If POEs hired the same portion of highly educated employees (those with a first college degree and above) as SOEs, they would have produced more quality-adjusted patents in the years prior to 2009 from the same R&D expenditure.

4. Decomposing contributions to the SOE-POE innovation gap

The descriptive statistics show there are economically and statistically significant differences in innovation activity, productivity, and productivity growth between SOEs and POEs, observed before and after the 2009 fiscal stimulus. Following the fiscal stimulus, the positive SOE-POE innovation activity and productivity growth differential significantly increase, and there is a positive rather than pre-stimulus negative SOE-POE productivity level differential. However, our panel regressions show that when we condition a firm's innovative activity on its skill ratio, subsidies, and financing cost, the effect of state ownership can become negative–as in the case of quality adjusted patenting prior to the fiscal stimulus–or statistically insignificant, as it does after the fiscal stimulus is implemented for quality adjusted patenting, and in both sub-periods for R&D expenditures. We now further explore these latter features of the data. Specifically, we decompose the SOE-POE innovation and productivity gaps in a mediation analysis to refine our understanding of the role of skill ratios, subsidies, and financing cost in accounting for observed SOE-POE innovation and productivity disparities. Figure 4 represents the framework for the mediation analysis.

Path c in the upper panel of figure 4 represents the total effect of state ownership on the dependent variable Y, which is innovation activity of a firm measured by either quality-adjusted patenting or size-adjusted R&D expenditure. Path a_i (a_1, a_2, and a_3) in the lower panel of figure 4 represents the effect of state ownership on each mediator, M^i (M^1, M^2, and M^3), where the mediators are the skill ratio, subsidies, and financing cost of the firm. Path b_i(b_1, b_2, and b_3) in the lower panel of figure 4 represents the effect of each mediator M^i (M^1, M^2, and M^3) on the dependent variable, innovation activity. Path c' represents the direct effect of state ownership on the dependent variable Y after controlling for the effects of mediators.

Figure 4: Mediation Analysis for firm innovation activity



In the statistical models that we estimate, the paths a_i(a_1, a_2, and a_3) are derived from regressing each mediator–skill level, subsidies, and interest cost–on a SOE dummy variable. That is, for all firms *f* in our sample, and each date *t*, we regress mediator *i* (skill ratio, subsidies, interest cost) on a constant, controls, and the SOE dummy:

$$M^i_{f,t} = \beta_i + a_i SOE_f + controls_{f,t} + \varepsilon^{M^i}_{f,t} \tag{7}$$

The effect of each mediator, M^i, on firm *f* innovation activity at date *t*, $Y_{f,t}$, and the conditional effect of state ownership of firm SOE_f on its innovation activity at date *t*, $Y_{f,t}$, are derived from the regressions

$$Y_{f,t} = \beta_Y + c'SOE_f + \sum_{i=1}^{3} b_i M^i_{f,t} + controls_{f,t} + \varepsilon^Y_{f,t} \tag{8}$$

In each regression, *controls* are additional variables which might affect either the mediators or innovation activity of firm *f* or both. We add capital intensity, log of employment, firm age, and firm industry-year-location fixed effects. The indirect effect of state ownership on innovation activity through mediator M^i is measured by the product $a_i \times b_i$. The total indirect effect of state ownership on innovation activity is then $\sum_{i=1}^{3} a_i \times b_i$. Tables 3 and 4 present the results.

Table 3 shows the results of an OLS regression of each mediator on the constant SOE_f firm dummy, from regression equation (7). The row of numbers in table 3 shows the effect of state ownership on a firm's skill ratio, subsidies, and interest cost. The first three columns present the effects in the pre-2009 sample and the second three columns in the post-2009 sample. State ownership has a positive effect on both a firm's skill ratio and subsidies, even after controlling firm size, age, capital intensity and industry-year-location effects, and a negative effect on financing cost (measured by the interest fee to total debt ratio). In other words, a_i is positive for a firm's skill ratio and subsidies and negative for its financing cost. All of the effects are highly statistically significant. The impact of state ownership for subsidies received by the firm rises markedly in the post-stimulus data, and the effect of state ownership for interest costs borne by a firm is more negative in the post-stimulus data. These results suggest the stimulus provided higher subsidies and cheaper credit for SOEs.

Table 3. Mediation analysis: impact of state ownership on mediators (equation (7))

	Pre 2009			Post 2009		
	skill ratio (a_1)	**subsidies** (a_2)	**interest** (a_3)	**skill ratio** (a_1)	**subsidies** (a_2)	**interest** (a_3)
SOE_f	0.0619***	0.1274***	-0.0108**	0.0619***	0.2637***	-0.0134***
	(0.0016)	(0.0097)	(0.0036)	(0.0030)	(0.0181)	(0.0012)

Notes: Mediation analysis for the merged ASM-SIPO sample from 2003 to 2011. Sample excludes all foreign owned firms, firms that changed ownership during the sample period, and firms that operate fewer than three consecutive years. Robust standard errors are clustered at the industry-year-location level and reported in parentheses. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% levels, respectively.

Table 4 shows the results of regressing a firm's quality adjusted patent applications on the constant SOE_f firm dummy and the mediators. as in equation (8). The table thus shows the estimated values of the direct, conditional effect of state ownership for innovation, c', and the effects of the mediators, $b_i(b_1, b_2,$ and $b_3)$. Considering first the impact of state ownership conditional on the mediators, shown in the first row of numbers for the pre and post-2009 sample periods, we see that state ownership has a *negative* direct effect for quality-adjusted patent applications before 2009 (we also found this in some of our earlier panel regressions in table 2) and a small positive direct effect in the period after 2009 which is not significantly different from zero. Note that, since we include only firms with constant ownership in the regressions, there is no possibility of reverse causality of patent applications (or mediators, for that matter) for ownership status. The second and third rows show that skill ratios and subsidies are positively and significantly associated with a firm's innovation output, conditioning on a firm's state ownership status, and in both sub-periods. The size of these positive effects becomes larger after 2009. The fourth row of numbers shows that interest cost is not significantly associated with a firm's patent applications before 2009 and negatively and significantly associated with a firm's patent applications after 2009. Again, these effects are conditioned on the firm's ownership status.

Table 4. Mediation analysis: impact of state ownership and mediators for innovation (equation (8))

	Pre 2009	Post 2009
	Quality adjusted patent application	Quality adjusted patent application
SOE_f (c')	-0.0459***	0.0043
	(0.0092)	(0.0218)
Skill ratio (b_1)	1.1015***	1.2146***
	(0.0190)	(0.0415)
Subsidies (b_2)	0.0546***	0.0935***
	(0.0031)	(0.0069)
Interest cost (b_3)	0.0191	-0.2218***
	(0.0158)	(0.0959)

Note: see notes from Table 3.

Table 5 computes the total indirect effect of state ownership for innovative activity of firms via each of the mediator variables–the product $\boldsymbol{a_i \times b_i}$. Table 6 shows the share of the total indirect effect of state ownership attributable to each mediator, $\frac{\boldsymbol{a_i \times b_i}}{\boldsymbol{\sum_{i=1}^{3} a_i \times b_i}}$. A firm's skill ratio contributes the most to the indirect effect of state ownership, and financing cost contributes the least – in fact its indirect effect is not statistically significantly different from zero in the pre-2009 sample period. The contributions from subsidies and financing cost increase after 2009, although the latter remains small and is positive (recall that state ownership tends to reduce interest costs after 2009 in table 3). Table 6 shows that subsidies contribute 9.28 percent to the indirect effects of state ownership for innovation in the pre-2009 sample, but 23.98 percent in the post-2009 sample. The role of the skill ratio exhibits a corresponding decline in the post-2009 sample.

The total effect of state ownership on patent applications can be computed as the sum of c' and the total indirect effects summed over mediators, $\boldsymbol{\sum_{i=1}^{3} a_i \times b_i}$. Using the numbers from tables 4 and 5 the total effect of state ownership for quality adjusted patenting in the pre-2009 sample is 0.029, and in the post-2009 sample is 0.107. Notice that in the pre-2009 sample, the direct effect of state ownership is negative. One explanation for the direct effect to be negative is that SOE productivity levels are relatively small compared to POEs before 2009, which could be associated with lower patenting by SOEs. The summary statistics in table 1 showed that in the pre-2009 sample, on average, SOEs' productivity is only 87.8% of POEs' productivity. However, SOE productivity became larger than POE productivity in the post-2009 sample; at the same time, the direct effect of state ownership for quality-adjusted patenting became positive. Note that when c and c' have the same sign in the post-2009 sample period, one can calculate the proportion of the total SOE effect for innovation that is mediated, and it is 96 percent.

Table 5. Mediation analysis: total indirect impact of state ownership through each mediator ($a_i \times b_i$)

	Pre 2009	Post 2009
	Quality adjusted patent application	Quality adjusted patent application
Skill ratio $(a_1 \times b_1)$	0.0682***	0.0752***
	(0.0026)	(0.0055)
Subsidies $(a_2 \times b_2)$	0.0070***	0.0247***
	(0.0006)	(0.0026)
Interest cost $(a_3 \times b_3)$	-0.0002	0.0030***
	(0.0078)	(0.0012)

Notes: see notes from Table 3.

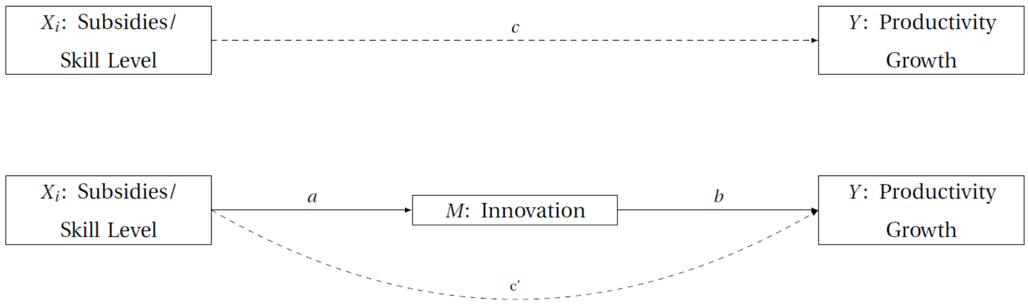
Table 6. Mediation analysis: share of total indirect impact of state ownership of each mediator ($\frac{a_i \times b_i}{\sum_{i=1}^{3} a_i \times b_i}$)

	Pre 2009	Post 2009
	Quality adjusted patent application	Quality adjusted patent application
Skill ratio $(a_1 \times b_1)$	0.9099	0.7313
Subsidies $a_2 \times b_2)$	0.0928	0.2398
Interest cost $(a_3 \times b_3)$	-0.0028	0.0289

Notes: see notes from Table 3

The mediation analysis shows that the innovation gap between SOEs and POEs can be largely explained by differences in their skill ratio and in the government subsidies they receive. Endogenous growth theory suggests that innovation is the main driver of productivity growth. The observed higher productivity growth in SOEs could be explained by their higher levels of innovation activities –which are strongly influenced by SOE-POE subsidy and skill ratio differences. This section analyzes whether differences in skill levels and subsidies contribute directly and/or indirectly through firm innovation activities to the observed SOE-POE differential in productivity growth, and hence whether and to what extent the SOE-POE innovation differential can help explain SOE "catch up" with POEs in productivity levels. To do so, we conduct a similar mediation analysis as we did for the impact of state ownership for innovation. Figure 5 represents the framework of the productivity mediation analysis. The outcome variable, Y is firm productivity growth, which is measured by firm TFP growth. The mediator is innovation activity, which is measured by the quality-adjusted number of granted invention and utility model patents that a firm applied for within a given year. Its skill ratios and subsidies can directly affect the productivity growth of a firm, or indirectly as a result of the higher innovation activity they are associated with.

Figure 5: Mediation Analysis: Productivity Growth



In the statistical models that we estimate, path c is derived by regressing directly firm productivity growth on each of skills and subsidies separately. The paths $a_i(a_1, a_2)$ are derived from regressing innovation activity on (in separate regressions) skill levels and subsidies. That is, for all firms *f* in our sample, and each date *t*, we regress the mediator innovation, $M_{f,t}^{inn}$, on a constant, controls, and either skill levels, or subsidies,

$$M_{f,t}^{inn} = \beta_{inn} + a_1 skill_{f,t} + controls_{f,t} + \varepsilon_{f,t}^{M^{inn}} \qquad (9a)$$

$$M_{f,t}^{inn} = \beta_{inn} + a_2 subs_{f,t} + controls_{f,t} + \varepsilon_{f,t}^{M^{inn}} \qquad (9b)$$

The conditional direct effect for firm *f* productivity growth at date *t*, $Y_{f,t}$, of skills and subsidies, and the conditional effect of its innovation, $M_{f,t}^{inn}$, are derived from the regressions

$$Y_{f,t} = \beta_Y + c'_1 skill_{f,t} + bM_{f,t}^{inn} + controls_{f,t} + \varepsilon_{f,t}^{Y} \qquad (10a)$$

$$Y_{f,t} = \beta_Y + c'_2 subs_{f,t} + bM_{f,t}^{inn} + controls_{f,t} + \varepsilon_{f,t}^{Y} \qquad (10b)$$

In each regression, *controls* are additional variables which might affect either a firm's innovation activity or its skill ratio and subsidies it receives. We add capital intensity, log of employment, TFP level, and firm industry-year-location fixed effects. The indirect effect of skills or subsidies on productivity growth through the innovation mediator M^{inn} is measured by the product $a_i \times b, i = 1,2$. Table 7 summarizes all results from estimating regression equations (9a) through (10b), as well as the regression equations in which we estimate the direct paths from skills and subsidies to productivity growth.

Column (1) in table 7 shows the estimated total effect of subsidies and skill levels for the productivity growth of a firm. Both variables are positively associated with productivity growth and the effects are statistically significant. Column (2) shows the direct effect of skill ratio or subsidies on a firm's productivity growth, conditional on innovation, estimated in equations (10a) and (10b). Once we control for innovation–the

Table 7: Mediation Analysis - Productivity Growth

	(1) *C*	(1) *c'*	(2) *A*	(3) *b*	(4) $a \times b$	(5) $\frac{ab}{c}$
subsidies	0.0039**	0.0032	0.0613***	0.0200***	0.0012***	0.3144
	(0.0016)	(0.0021)	(0.0032)	(0.0028)	(0.0002)	
skill ratio	0.0236**	0.0222	0.7184***	0.0205***	0.0147***	0.6240
	(0.0093)	(0.0137)	(0.0206)	(0.0028)	(0.0021)	

Note: Mediation analysis for the merged ASM-SIPO sample from 2003 to 2011. The sample excludes all foreign owned firms, firms that changed ownership during the sample period, and firms that operated for less than three consecutive years. Column (1) shows the total effect of a firm's skill ratio or subsidies on a firm's productivity growth, which is the sum of all other effects. Column (2) shows the direct effect of skill ratio or subsidies on a firm's productivity growth, conditional on innovation. Column (3) shows the effect of skill or subsidies for a firm's innovation from equations (9a) and (9b). Column (4) shows the effect of innovation on productivity growth, conditional on skills and subsidies. Column (5) shows the indirect effect of skill level or subsidies on a firm's productivity growth through its innovation activities. Robust standard errors clustered at year-location-industry level are reported in parenthese. $***$, $**$ and $*$ indicate significant level at 1%, 5% and 10%, respectively

mediator–the impact of subsidies and skill ratio for firm productivity growth become statistically insignificant. Column (3) shows the effect of skill or subsidies for a firm's innovation, the mediator, from estimating equations (9a) and (9b); it documents a strong positive effect of a firm's skill ratio and its subsidies on its innovation activity. Column (4) shows the effect of innovation on productivity growth, conditional on skills and subsidies respectively. It shows a positive and statistically significant relationship between innovation and productivity growth whether we condition on skills or subsidies. A one standard deviation increases in granted patents is associated with roughly a 2 percent increase in productivity growth, whether we condition on skills or subsidies of the firm. Column (5) shows the implied indirect effect of skills and subsidies for productivity growth; the product of paths a_i and b. It shows statistically significant indirect effects of skill levels and subsidies on productivity growth through innovation activities, despite the insignificant direct effects we estimated. A one standard deviation increase in subsidies would result in a 1.2 percent indirect increase in productivity growth by raising the number of granted patents, and a one standard deviation increase in the skill ratio would results in a 1.5 percent indirect increase in productivity growth by raising the number of granted patents. The skill ratio of a firm contributes more to its productivity growth than subsidies. Given the insignificance of the estimates of direct effects it is difficult to reconcile the total effect with the sum of indirect and direct effects of skills and subsidies, however, we present the portion of path c accounted for by indirect effects in column 5.

The empirical evidence presented here suggests that the observed increase in productivity growth among SOEs following the fiscal stimulus policy can be attributed to an increase in the subsidies they received. Nonetheless, as the skill ratio contributes most to a firm's innovation activities, higher skill ratios in SOEs can explain the larger magnitude of patent applications and granted patents among SOEs, and faster productivity growth in SOEs. The documented "shrinking gap" in productivity levels between SOEs and POEs can be partially explained by the differential in their innovation activities, which results from their different skill levels and received subsidies. In short, if private firms hired the same number of highly educated workers (those with college degree and above), or received the subsidies as SOEs do, they would enjoy much higher productivity growth.

5. Empirical evidence on local crowding out

In this section, we follow Huang et al (2016)'s specification to estimate local crowding-out of private firm innovation activity. China's banking system is geographically segmented. Inter-province lending was prohibited in China before 2006 and needs special licenses which were seldom issued by the regulator after 2006. Thus, local branches of China's five largest state-owned banks–rural and city banks–are subject to high political pressure to finance local government debts and local state-owned enterprises' debts (Huang et al, 2016). As inter-province or inter-city lending is seldom allowed, an increase in local government/SOE debt level reduces borrowing opportunities for private firms, crowding out their investment and innovation activity.

We estimate this local crowding out hypothesis using the following specification:

$$Pat_{ict} = \beta_0 + \beta_1 SOE + \beta_2 LGD_{ct} + \beta_3 SOE \times LGD_{ct} + X_{ict}\Gamma + \xi_i + \tau_t + \eta_c + \varepsilon_{ict}. \qquad (11)$$

In (11), Pat_{ict} is the ratio of quality-adjusted patent applications for invention and utility model to the real capital ratio, for firm *i* in city *c* in year *t*. SOE is a dummy variable equal to 1 if the firm is a state-owned enterprise. LGD is the ratio of local government debt to local GDP ratio in city *c* in year *t*. Most of the local government debt is financed by local banks and the loans are used to finance local infrastructure projects and subsidize SOEs (Huang et al, 2016; Chen et al, 2020). X_{ict} is a set of firm-level controls including firm age, capital intensity, and employment. Finally, ξ_i, τ_t and η_c are the firm fixed effect, year fixed effect, and city fixed effect respectively. We cluster the standard error at the firm and city-year level to capture any unobserved variation within firms, location, and year. Table 8 reports the regression results of equation (11) and its variations.

Column (1) of Table 8 shows a significant negative correlation between local government debt and local firms' innovation activity. This estimated correlation is unchanged if we include the SOE dummy. Column (3) is the estimation results of equation 11, in which we include the interaction of SOE and the local government debt-to-GDP ratio. As state-ownership is controlled, β_2 measures the average impact of local government debt on innovation activity (measured as non-design patent applications over the real capital stock) among POEs. The interaction term β_3 captures the difference of this impact between SOEs and POEs. The sum of $\beta_2 + \beta_3$ measures the average impact of local government debt on SOE innovation activity. Column (3) indicates an economically strong and statistically significant negative impact of local government debt on POE innovation activity, but a significant and positive impact on SOE innovation activity. A 10 percent increase in local government to debt ratio is associated with, on average, a 0.8 percent decrease in invention and utility application to capital ratio among POEs; whereas, on average a 1.66 percent increase in invention and utility application to capital ratio among SOEs. From column (4) to (6), we replace the dependent variable with patent applications to capital in three different categories: invention, utility model, and industrial design. The estimation results indicate that the local crowding out effect (or innovation disparity) is strongest for invention patents and least strong for industrial design.

Table 9. Correlation between Local Government Debt and Innovation Activity

	Invention + Utility / capital stock			Invention	Utility	Design
	(1)	(2)	(3)	(4)	(5)	(6)
SOE		0.001	-0.000	0.000	-0.000	-0.001**
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LGD	-0.040*	-0.040*	-0.079***	-0.059***	-0.061***	-0.024***
	(0.021)	(0.022)	(0.017)	(0.012)	(0.014)	(0.008)
SOE*LGD			0.166***	0.137**	0.131***	0.081***
			(0.049)	(0.055)	(0.022)	(0.009)
N Obs	110,825	110,825	110,825	98,602	99,704	98,162
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.427	0.427	0.427	0.419	0.504	0.431

Note: Sample period: 2003 to 2011. The sample contains patentee only. In each regression, capital intensity, firm age, firm size measured by the log of employment, firm fixed effect, year-city fixed effects are included but not reported. Robust standard errors double clustered at firm and year-city level are reported in parentheses. $***$, $**$ and $*$ indicate significant level at 1%, 5% and 10%, respectively.

6. Model

Our model is an extension of a Schumpeterian growth model developed by Aghion and Howitt (1998), with two key differences: 1) There are two sectors with uninterchangeable technologies; 2) one sector faces financial frictions when raising funds for capital investment.

6.1 Final Goods

There is one final good produced by a representative final goods producer using differentiated intermediate goods. The production technology is:

$$Y_t = \int_0^1 A_{s,it} x_{s,it}^{\alpha} \, di + \int_0^1 A_{p,it} x_{p,it}^{\alpha} \, di \, . \tag{12}$$

In (12), $x^{\alpha}_{s,it}$ is the quantity of intermediate goods produced by state-owned enterprises (SOEs) and $A_{s,it}$ is the associated productivity. Similarly, $x^{\alpha}_{p,it}$ is the quantity of intermediate goods produced by privately-owned enterprises (POEs) and $A_{p,it}$ is the associated productivity. Here, $\alpha \in (0,1)$ measures returns to scale and is positively associated with the degree of substitutability between different intermediate goods produced by the same type of enterprise. We let the final good be the numeraire.

The optimization problem of the final goods producer yields inverse demand function for each intermediate good produced by SOEs or POEs:

$$\alpha A_{q,it} x^{\alpha-1}_{q,it} = p_{q,it}, \quad q \in \{s, p\}. \tag{13}$$

The final good can be used for consumption, investment in capital goods, or R&D inputs.

6.2 Intermediate Goods Producers

There are two type of firm, SOEs and POEs, with a continuum of firms and associated intermediate products, *i,* of each type located on the unit interval. SOEs and POEs are monopolists. Each intermediate good, *i*, is exclusively produced by firm *i* using physical capital with production technology:

$$x_{q,it} = \frac{K_{q,it}}{A_{q,it}}, \;\; q \in \{s, p\}. \tag{14}$$

In (14), $K_{q,it}$ is capital input of monopolist *i* from sector *q*. The cost function of each incumbent monopolist is $\xi_{q,t} K_{q,it}$. Here $\xi_{q,t}$ is the user price for each unit of capital input. Following Aghion and Howitt (1998), $\xi_{q,t}$ equals real interest rate charged on capital inputs (r_t) plus the capital depreciation rate (δ) and minus the subsidy rate to the holding of capital (β_k). Thus, for SOEs, which receive a capital subsidy, we have:

$$\xi_{s,t} = r_t + \delta - \beta_k.$$

We assume that POEs do not receive any capital subsidy. In addition, the interest rate charged on each POEs' capital input is different from the real interest rate, r_t, charged to SOEs. Following Cong et al (2020), we assume the real interest rate charge on capital input among POEs is φr_t, with $\varphi \geq 1$[2]. We view φ as a measure of financial frictions; a higher φ indicates greater friction in the financial market confronted by POEs relative to SOEs. Thus, the usage price for each unit of capital input for a POE can be written as:

$$\xi_{p,t} = \varphi r_t + \delta.$$

[2] Consider a risk-neutral bank that supplies credit to both POEs and SOEs. Let $r_{s,t}$ be the real interest rate charged on loans lend to SOEs and $r_{p,t}$ be the real interest rate charged on loans lend to POEs. Suppose firms survive with probability μ in each instant. If SOEs go bankrupt, the government will bailout them out, allowing them to survive, with probability b. The expected profit for a bank of lending L units to SOEs is: $r_{s,t}L[\mu + (1-\mu)b]$ and the expected profit of lending L units to POEs is: $r_{p,t}L\mu$. The bank will set $r_{p,t}$ and $r_{s,t}$ until the expected payoff from lending to SOEs equals the expected payoff from lending to POEs. That is: $r_{s,t}L[\mu + (1-\mu)b] = r_{p,t}L\mu$. Rearranging, we have $r_{p,t} = \left[1 + \frac{(1-\mu)b}{\mu}\right] r_{s,t} = \varphi r_{s,t}$

The optimization problem of each intermediate good producer is to maximize profit by choice of production plan subject to the demand function of the final good producer, equation (13),

$$\max_{x_{q,it}} \ p_{q,it}x_{q,it} - \xi_{q,t}x_{q,it}A_{q,it}, \qquad q \in \{s,p\}$$

$$s.t. \ \ p_{q,it} = \alpha A_{q,it}x_{q,it}^{\alpha-1} .$$

The optimal quantity of each intermediate good produced is:

$$x_{q,it} = \alpha^{\frac{2}{1-\alpha}}\xi_{q,t}^{\frac{-1}{1-\alpha}}, \ \ q \in \{s,p\}. \tag{15}$$

Our assumption on the production technology of intermediate goods ensures that the optimal quantity of intermediate goods in (15) is independent of productivity, $A_{q,it}$. It also implies that higher productivity firms accumulate a higher capital stock. The profit flow for each intermediate good can be written as:

$$\pi_{q,it} = p_{q,it}x_{q,it} - \xi_{q,t}x_{q,it}A_{q,it} = \tilde{\alpha}A_{q,it}\xi_{q,t}^{-\frac{\alpha}{1-\alpha}}, \ \ q \in \{s,p\}, \tag{16}$$

with $\tilde{\alpha} \equiv (1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}$. Profit is increasing with productivity $A_{q,it}$, and decreasing with the user cost of capital.

6.3 Innovation Activity

In each sector, entrepreneurs can improve average productivity by using final goods as R&D inputs. Let ϕ be the Poisson arrival rate of innovation:

$$\phi_{q,t} = \lambda_q \frac{N_{q,t}}{A_{q,t}^{max}}, \qquad q \in \{s,p\}. \tag{17}$$

In (17), λ_q is the productivity of R&D inputs in sector q, $N_{q,t}$ is the number of final goods used as R&D inputs, and $A_{q,t}^{max}$ is the leading-edge technology in each sector, and defined as

$$A_{q,t}^{max} \equiv \max\{A_{q,it} \big| i \in (0,1)\}, q \in \{s,p\}. \tag{18}$$

Note from (17) and (18) that innovation arrival rates and outcomes are identical for all innovators within a sector. We use the functional form of the Poisson arrival rate in (17) to account for the fact that the cost of innovation increases proportionally as technology advances. We also make the strong assumption that innovation technology is not diffused between the POE and SOE sectors. That is, the technology embodied in the two sectors is not interchangeable.

Each successful innovation results in an enterprise attaining the leading-edge technology and replacing an incumbent randomly. Incumbents do not innovate. The value of successful innovation can be written as:

$$V_{q,it} = \int_t^\infty e^{-\int_t^\tau (r_b+\phi_b)db}\pi_{q,i\tau}d\tau, \ \ q \in \{s,p\}. \tag{19}$$

In (19), $\pi_{q,i\tau}$ is the flow of profit for incumbent *i* which uses the leading-edge technology and, specifically, $\pi_{q,i\tau} = \pi_{q,\tau} = \tilde{\alpha} A_{q,\tau}^{max} \xi_{q,\tau}^{-\frac{\alpha}{1-\alpha}}$. In addition, r_b is the instantaneous rate of interest charged to SOEs in instant *b*, $r_b = r_{s,b}$, ϕ_b is the instantaneous creative destruction rate, the probability of an incumbent being displaced by an innovation, and the discount rate for the value of innovation is the sum of these. Let $\beta_{q,n}$ be the subsidy rate for innovation. The total cost of investing $N_{q,t}$ final goods as R&D input is then $(1 - \beta_{q,n})N_{q,\tau}$. Using these results, the zero-entry or no arbitrage condition for innovators in each sector–that the marginal cost and gain from innovation be equal–is

$$1 - \beta_{q,n} = \frac{\lambda_q}{A_{q,t}^{max}} \int_t^{\infty} e^{-\int_t^{\tau}(r_b+\phi_b)db} \pi_{q,i\tau} d\tau = \lambda_q \frac{\tilde{\alpha}\xi_{q,t}^{-\frac{\alpha}{1-\alpha}}}{r_t + \lambda_q \frac{N_{q,t}}{A_{q,t}^{max}}}, \quad q \in \{s,p\}. \tag{20}$$

Solving (20) for the optimal investment in R&D in each sector we obtain,

$$N_{q,t} = A_{q,t}^{max} \left(\frac{\tilde{\alpha}\xi_{q,t}^{-\frac{\alpha}{1-\alpha}}}{1 - \beta_{q,n}} - \frac{r_t}{\lambda_q} \right), q \in \{s,p\}. \tag{21}$$

Optimal R&D investment, (21), increases with the productivity of R&D in the sector, λ_q, and the innovation subsidy rate $\beta_{q,n}$. Optimal R&D investment is decreasing in the user cost of capital $\xi_{q,t}$, as a higher user cost reduces the expected profit flow and marginal benefit of innovation.

6.4 Households

We assume a representative household with CRRA utility function and endowed with initial asset E_0. Household optimization problem is standard:

$$\max_{C_\tau, S_\tau} \int_t^{\infty} e^{-\rho\tau} \left(\frac{C_\tau^{1-\varepsilon} - 1}{1 - \varepsilon} \right) d\tau. \qquad s.t. \;\; C_\tau + \dot{S}_\tau \leq r_\tau S_\tau \tag{22}$$

Here $\varepsilon > 0$ measures the degree of relative risk aversion. The household Euler equation is:

$$\dot{C}_t^{-\varepsilon} = (\rho - r_t) C_t^{-\varepsilon}. \tag{23}$$

6.5 Detrending and the growth rate

Following Caballero and Jaffe (1993) and Aghion and Howitt (1998), we assume that leading-edge technology in each sector grows at a rate proportional to the rate of innovation in each sector. Let $g_{s,t}$ (or $g_{p,t}$) be the growth rate of leading-edge technology in the SOE (POE) sector,

$$g_{q,t} \equiv \frac{\dot{A}_{q,t}^{max}}{A_{q,t}^{max}} = \sigma\phi_{q,t} = \frac{\sigma\lambda_q N_{q,t}}{A_{q,t}^{max}}, \qquad \forall q \in \{s,p\}. \tag{24}$$

In (24), $\sigma > 0$ measures the impact of innovation on the aggregate knowledge stock in both sectors. Let $A_{q,t} = \int_0^1 A_{q,it}di$ be the average productivity in each sector *q*. It is easy to show that the ratio of $\frac{A_{q,t}^{max}}{A_{q,t}}$ will converge to $1+\sigma$. Without loss of generality, we assume that $A_{q,t}^{max} = (1+\sigma)A_{q,t}$. Thus, $g_{q,t}$ is also the growth rate of average productivity in each sector. Let $A_t = \int_0^1 A_{s,it}di + \int_0^1 A_{p,it}di$ be aggregate productivity. Then the growth rate of aggregate productivity can be written as:

$$g_t \equiv \frac{\dot{A}_t}{A_t} = \frac{\dot{A}_{s,t}^{max} + \dot{A}_{p,t}^{max}}{A_{s,t}^{max} + A_{p,t}^{max}} = \frac{\sigma\left(\lambda_s N_{s,t} + \lambda_p N_{p,t}\right)}{A_{s,t}^{max} + A_{p,t}^{max}}. \tag{25}$$

We detrend each aggregate variable with aggregate productivity A_t, and each sector-specific variable with the average productivity in associated with that sector, $A_{q,t}$. We detrend R&D input by the leading-edge productivity in each sector $A_{q,t}^{max}$. That is:

$$c_t = \frac{C_t}{A_t}, \quad n_{q,t} = \frac{N_{q,t}}{A_{q,t}^{max}}, \quad k_{q,it} = \frac{K_{q,it}}{A_{q,t}}.$$

The household Euler equation can then be written in terms of detrended consumption as:

$$\frac{\dot{c}_t}{c_t} = \frac{r_t - \rho}{\varepsilon} - g_t. \tag{26}$$

Define $\omega_t \equiv \frac{A_{p,t}^{max}}{A_{s,t}^{max} + A_{p,t}^{max}} = \frac{A_{p,t}}{A_{s,t}+A_{p,t}}$ as the weight of the POE sector's innovation contribution to aggregate productivity growth. The aggregate growth rate can therefore be written as

$$g_t = (1-\omega_t)\sigma\lambda_s n_{s,t} + \omega_t\sigma\lambda_p n_{p,t}.$$

6.6 Steady state analysis

In a steady state of the transformed (detrended) economy, $\frac{\dot{c}_t}{c_t} = 0$. Using (21), (25), and (26), the economy is characterized by the following four equations with four unknowns n_s, n_p, g and r:

$$g = \sigma\left(\lambda_s n_s(1-\omega) + \lambda_p n_p \omega\right), \tag{27a}$$

$$r = \rho + \varepsilon g, \tag{27b}$$

$$1 - \beta_{s,n} = \lambda_s \frac{\tilde{\alpha}(r + \delta - \beta_k)^{-\frac{\alpha}{1-\alpha}}}{r + \lambda_s n_s}, \tag{27c}$$

$$1 - \beta_{p,n} = \lambda_p \frac{\tilde{\alpha}(\varphi r + \delta)^{-\frac{\alpha}{1-\alpha}}}{r + \lambda_p n_p}. \tag{27d}$$

Given the parameters $\{\lambda_s, \lambda_p, \beta_k, \beta_{s,n}, \beta_{p,n}, \rho, \varepsilon, \alpha, \sigma, \varphi\}$, we can solve for the four unknowns $\{r, n_s, n_p, g\}$.

Assumptions. Parameters satisfy:

$$A1.\, \beta_k < \rho + \delta.$$

$$A2.\, (\rho + \delta - \beta_k)^{\frac{\alpha}{1-\alpha}} > \frac{\tilde{\alpha}}{1 - \beta_{s,n}} \frac{\lambda_s}{\rho}.$$

$$A3.\, (\rho\varphi + \delta)^{\frac{\alpha}{1-\alpha}} > \frac{\tilde{\alpha}}{1 - \beta_{p,n}} \frac{\lambda_p}{\rho}.$$

Comment. A1 ensures that the user cost of capital is always positive. A2 and A3 ensure a positive solution for R&D investment in each sector, i.e. $n_{s,t} > 0$ and $n_{p,t} > 0$.

Proposition I. Given the equilibrium real interest rate, productivity-adjusted capital investment is at least as high in the SOE sector than in the POE sector. That is: $k_{s,it} \geq k_{p,it}$.

Proof. From profit maximization of SOE and POE intermediate good producers, respectively

$$k_{s,i} = k_s = \alpha^{\frac{2}{1-\alpha}} (r + \delta - \beta_k)^{-\frac{\alpha}{1-\alpha}} \ \forall i,$$

$$k_{p,i} = k_p = \alpha^{\frac{2}{1-\alpha}} (\varphi r + \delta)^{-\frac{\alpha}{1-\alpha}} \ \forall i.$$

Then if $\varphi > 1$ and $\beta_k > 0, r + \delta - \beta_k < \varphi r + \delta$, and $k_{s,i} > k_{p,i}$. If $\varphi = 1, \beta_k = 0$, then $k_{s,i} = k_{p,i}$. ■

Proposition II. In the absence of subsidies and financial friction, that is: $\varphi = 1$ and $\beta_k = \beta_{s,n} = \beta_{p,n} = 0$, the R&D investment and average productivity growth rate is higher in the sector with higher R&D efficiency.

Proof. The solution for leading-edge technology-adjusted R&D input in each sector can be written as

$$\lambda_s n_s = \frac{\tilde{\alpha}\lambda_s}{1 - \beta_{s,n}} (r + \delta - \beta_k)^{-\frac{\alpha}{1-\alpha}} - r,$$

$$\lambda_p n_p = \frac{\tilde{\alpha}\lambda_p}{1 - \beta_{p,n}} (\varphi r + \delta)^{-\frac{\alpha}{1-\alpha}} - r.$$

With $\varphi = 1$ and $\beta_k = \beta_{s,n} = \beta_{p,n} = 0, n_q = \tilde{\alpha}(r + \delta)^{-\frac{\alpha}{1-\alpha}} - \frac{r}{\lambda_q}, q \in \{s, p\}$. It is immediate that, given r, n_q is an increasing function of λ_q. Hence, sectors with higher R&D productivity invest more in R&D. In addition, the equilibrium growth rate in each sector can be written $g_q = \sigma\lambda_q n_q, q \in \{s, p\}$. Thus, g_q is an increasing function of λ_q and n_q. The average productivity growth rate is unambiguously higher in sectors with a higher λ_q. ■

Comment on misallocation and growth. Proposition II implies that even if R&D efficiency is lower in SOEs than POES, $\lambda_s < \lambda_p$, the SOE sector can nonetheless have higher average productivity growth than the POE sector if there is a sufficiently high capital subsidy rate, relative SOE R&D subsidy rate, or financial friction confronted by POEs. Specifically, $\lambda_s n_s > \lambda_p n_p$ if $\frac{\lambda_s/\lambda_p}{(1-\beta_{s,n})/(1-\beta_{p,n})} > \left(\frac{r+\delta-\beta_k}{\varphi r+\delta}\right)^{\frac{\alpha}{1-\alpha}}$. In the presence of subsidies or financial frictions, innovation resources may be reallocated to the sector that is less efficient in innovation with an increase in subsidies or POE financial frictions. Hence, a less R&D efficient SOE sector can dominate the economy's R&D effort/inputs and exhibit a higher average growth rate than the POE sector, as a result of an increase in SOE capital subsidies or SOE R&D subsidies relative to POE R&D subsidies.

Proposition III. (Crowding out) In the steady state, an increase in the capital subsidy rate to SOEs crowds out capital investment and R&D investment in POEs. That is:

$$\frac{dn_s}{d\beta_k} > 0, \frac{dk_s}{d\beta_k} > 0, \frac{dn_p}{d\beta_k} < 0, \frac{dk_p}{d\beta_k} < 0.$$

Proof. Substituting out for g in the steady state aggregate growth rate equation, $g = (r-\rho)/\varepsilon$, and taking the derivative with respect to β_k on both sides of the other three equations, we get:

$$\sigma(1-\omega)\lambda_s \frac{dn_s}{d\beta_k} + \sigma\omega\lambda_p \frac{dn_p}{d\beta_k} = \frac{1}{\varepsilon}\frac{dr}{d\beta_k},$$

$$\frac{dr}{d\beta_k} + \lambda_s \frac{dn_s}{d\beta_k} = \Delta_s \left[\frac{dr}{d\beta_k} - 1\right],$$

$$\frac{dr}{d\beta_k} + \lambda_p \frac{dn_p}{d\beta_k} = \Delta_p \varphi \frac{dr}{d\beta_k},$$

where $\Delta_s \equiv -\frac{\alpha}{1-\alpha}(r+\delta-\beta_k)^{-1}(r+\lambda_s n_s) < 0$, $\Delta_p \equiv -\frac{\alpha}{1-\alpha}(\varphi r+\delta)^{-1}(r+\lambda_p n_p) < 0$. Solving for $\frac{dr}{d\beta_k}$, we get:

$$\frac{dr}{d\beta_k} = \frac{-\varepsilon\sigma(1-\omega)\Delta_s}{1+\varepsilon\sigma(1-\omega)(1-\Delta_s)+\varepsilon\sigma\omega\left(1-\Delta_p\varphi\right)}.$$

Since $1-\Delta_s > 0, 1-\Delta_p\varphi > 0$, and $\Delta_s < 0$, then $0 < \frac{dr}{d\beta_k} < 1$.

Then

$$\lambda_p \frac{dn_p}{d\beta_k} = \left(\Delta_p\varphi - 1\right)\frac{dr}{d\beta_k} < 0,$$

and

$$\lambda_s \frac{dn_s}{d\beta_k} = (\Delta_s - 1)\frac{dr}{d\beta_k} - \Delta_s = \Delta_s \left[\frac{\varepsilon\sigma(1-\omega)(1-\Delta_s)}{1+\varepsilon\sigma(1-\omega)(1-\Delta_s)+\varepsilon\sigma\omega\big(1-\Delta_p\varphi\big)} - 1\right] > 0.$$

For capital investment, given $0 < \frac{dr}{d\beta_k} < 1$, we have:

$$\frac{dk_s}{d\beta_k} \propto -(r+\delta-\beta_k)^{-\frac{1}{1-\alpha}}\left[\frac{dr}{d\beta_k} - 1\right] > 0,$$

$$\frac{dk_p}{d\beta_k} \propto -(\varphi r+\delta)^{-\frac{1}{1-\alpha}}\frac{dr}{d\beta_k} < 0. \blacksquare$$

Comment. An increase in the SOE capital subsidy rate reduces the marginal cost of capital and raises profit for each intermediate producer in the SOE sector. The raised profit increases the marginal benefit of SOE sector innovation, inducing higher SOE innovation. On the other hand, the increase in capital investment in the SOE sector raises the equilibrium interest rate and the user cost of capital charged to firms in the POE sector, which reduces the profit for each POE intermediate producer. Thus, innovation in the POE sector decreases with a reduction in the expected value of innovation.

Proposition IV. (Productivity growth at the sector and aggregate levels) In the steady state, an increase in the capital subsidy rate in the SOE sector raises the productivity growth rate in the SOE sector and reduces the productivity growth rate in the POE sector. At the aggregate level, the steady state growth rate increases with SOE capital subsidies. That is:

$$\frac{dg_p}{d\beta_k} < 0, \frac{dg_s}{d\beta_k} > 0, \frac{dg}{d\beta_k} > 0.$$

Proof. By the definition of g_p, g_s and $g = \frac{r-\rho}{\varepsilon}$, and using the results of proposition III,

$$\frac{dg_p}{d\beta_k} = \sigma\lambda_p \frac{dn_p}{d\beta_k} < 0,$$

$$\frac{dg_s}{d\beta_k} = \sigma\lambda_s \frac{dn_s}{d\beta_k} > 0,$$

$$\frac{dg}{d\beta_k} = \frac{1}{\varepsilon}\frac{dr}{d\beta_k} > 0. \blacksquare$$

Comment. From proposition III, an increase in the capital subsidy rate increases R&D investment in the SOE sector, raising the innovation rate and the productivity growth rate. However, the increase in SOE R&D investment crowds out R&D innovation in the POE sector, reducing the innovation rate as well as the productivity growth rate. The average productivity growth rate in the economy increases with the capital subsidy rate as the subsidy rate increase equilibrium real interest rate.

From footnote I, the financial friction parameter φ can be thought of as $\varphi = 1 + \left(\frac{1}{\mu} - 1\right) b$, where μ is the survival rate of firms and b is the probability of an SOE bailout by the government. Thus, φ is decreasing in the survival rate μ. We define a recession, as a reduction in the firm survival rate (that is, an increase in φ). Proposition V follows.

Proposition V. (Recessions) During a recession, POEs decrease their capital and R&D investment, reducing the equilibrium real interest rate. This increases capital and R&D investment among SOEs. However, the steady state growth rate of aggregate productivity is decreased.

Proof. Substituting for the steady state interest rate and taking derivatives with respect to φ on both side of the remaining three steady state equations,

$$\sigma(1-\omega)\lambda_s \frac{dn_s}{d\varphi} + \sigma\omega\lambda_p \frac{dn_p}{d\varphi} = \frac{1}{\varepsilon}\frac{dr}{d\varphi},$$

$$\lambda_s \frac{dn_s}{d\varphi} = (\Delta_s - 1)\frac{dr}{d\varphi},$$

$$\lambda_p \frac{dn_p}{d\varphi} = \left(\Delta_p\varphi - 1\right)\frac{dr}{d\varphi} + r\Delta_p.$$

With $\Delta_s < 0$ and $\Delta_p < 0$. Combining and rearranging,

$$\frac{dr}{d\varphi} = \frac{r\varepsilon\sigma\omega\Delta_p}{1 + \varepsilon\sigma(1-\omega)(1-\Delta_s) + \sigma\omega\left(1-\Delta_p\varphi\right)\varepsilon} < 0.$$

Therefore,

$$\lambda_s \frac{dn_s}{d\varphi} = (\Delta_s - 1)\frac{dr}{d\varphi} > 0,$$

$$\lambda_p \frac{dn_p}{d\varphi} = r\Delta_p\left(1 - \frac{\varepsilon\sigma\omega\left(1-\Delta_p\varphi\right)}{1 + \varepsilon\sigma(1-\omega)(1-\Delta_s) + \varepsilon\sigma\omega\left(1-\Delta_p\varphi\right)}\right) < 0.$$

In addition, using the expression for the optimal capital investments in the steady state,

$$\frac{dk_s}{d\varphi} \propto -\frac{dr}{d\varphi} > 0$$

$$\frac{dk_p}{d\varphi} \propto -\left(\frac{dr}{d\varphi}\varphi + r\right) = -\frac{1 + \varepsilon\sigma(1-\omega)(1-\Delta_s) + \varepsilon\sigma\omega}{1 + \varepsilon\sigma(1-\omega)(1-\Delta_s) + \varepsilon\sigma\omega\left(1-\Delta_p\varphi\right)} r < 0$$

Finally, the steady state growth rate declines,

$$\frac{dg}{d\varphi} = \frac{1}{\varepsilon}\frac{dr}{d\varphi} < 0. \blacksquare$$

Comment. Proposition V is consistent with Aghion et al (2012). R&D investment is procyclical when firms confront a financial friction but countercyclical when there is no financial friction. In our model, only firms in POE sector encounter financial frictions when raising capital funds. Proposition V implies that R&D investment in the SOE sector is counter cyclical (rises in a recession) whereas R&D investment in POE sector is procyclical (declines in a recession). During a recession, with an increase in financial friction, resources are reallocated from the POE sector to SOE sector.

7. Conclusion

In this paper, we have investigated the innovation behavior of SOEs and POEs in China before and following the 2009-2010 fiscal stimulus policy. Using merged ASM-SIPO-Google Patent data for Chinese manufacturing firms from the year 2003 to the year 2011, we document innovation disparities between SOEs and POEs. SOEs file more quality-adjusted patents than POEs, and the differential has widened since China's 4 trillion RMB fiscal stimulus policy in 2009 and 2010. We find that government subsidies and innovation capacities, measured by skill ratios, are the two main channels for the differential. Mediation analyses show that differences in subsidies and skill ratios across SOEs and POEs can explain as much as 90% of the observed difference in patent application between SOEs and POEs. Skill levels contribute the most to the difference in patent applications throughout the sample year, but the contribution of subsidies increased substantially after the 2009 fiscal stimulus policies. In addition, we find a large positive impact of subsidies on firm productivity growth which is explained by the role of subsidies in increasing a firm's successful patenting. The observed increase in productivity growth among SOEs after the fiscal stimulus, and relative to POEs, can be attributed to the rise in subsidies they received. Our empirical findings can partly explain the shrinking productivity gap between SOEs and POEs.

A natural extension of our work is to build an endogenous growth model which can quantify the stimulus policy's impact on aggregate growth and transition through reallocation of innovation activity across firms. Here we present preliminary qualitative results from a stylized model. In a steady state of the model, higher subsidies to SOEs for physical investment result in qualitatively the same increase in innovation, physical investment, and productivity growth in SOEs, and decline in those of POEs which do not receive subsidies, as we observe in our data. There is a crowding out effect of subsidies to SOEs for POE capital investment and innovation in the model, which operates through a higher interest cost of financing investment. We leave to future work a serious quantitative modeling exercise.

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Appendix

A.1. Sample Construction Details

We construct a panel data sample for Chinese manufacturing firms from 2003 to 2011. Data used in this paper are taken from three sources: 1) Chinese Annual Survey of Manufacturing (ASM). This dataset includes firms with annual sales greater than 5 million RMB (approximately USD800,000, after 2010, the ASM only contains firms with annual sales greater than 20 million RMB, approximately USD3,200,000); 2) Patent activities from China's State Intellectual Property Office (SIPO); and 3) Patent citations and claims data from Google Patent. The ASM contains detailed firm-level balanced sheet information such as output, employment, exports, fixed capital, compensation (wages paid and benefits provided) etc. Each Chinese firm has a unique identifying number which enables us to link firms over time. As some of the firm i.d. numbers are missing or changed in some years, following Brandt et al (2012), we also link firms by fuzzy matching with name, legal persons, telephone number, and location. SIPO provides detailed information on a firm's patent application date, patent granting date, number of applicators for a given patent, applier's information (firm name and location), and patent technology domain. These patent data are linked to the firm's data by the methodology proposed in He et al. (2016). However, SIPO does not provide qualified citation data, which is crucial to measure a firm's patent quality. To overcome this, we match the citation data in Google Patent to each SIPO patent. The citation data not only contains applicants' citations but also covers citations made by examiners and patent officers. The inclusion of examiner citations provides a better measurement for patent qualities. Google Patent also provides information on the time and technology domain when a patent is cited. This enables us to adjust a patent’s citation based on its time window and technology field. After adjustments, we can compare different patents over time and technology domains.

Unqualified observations in the merged sample are dropped according to criteria suggested by Cai and Liu (2009) and Feenstra (2013). These criteria include dropping observations that: 1) are missing key variables such as total assets, the net value of fixed assets, sales, and the gross value of firm output; 2) have fewer than 8 workers; 3) have annual sales less than 5 million RMB; 4) have invalid establishment time, namely, open month greater than 12 or less than 1 month, birth year later than survey year or earlier than 1700; and 5) exhibit conflicts in financial data. We also delete firms with the name "trading company" or "importing and exporting company" following Yu (2015). Firms that operate less than three consecutive years are dropped from the sample. The final merged sample contains 2,162,066 observations with 235,299 firms from the period 1998-2013. Among those firms, only 30,712 of them have filed at least one patent during our sample period. Firms in our sample applied for 1,298,068 patents from the year 1998 to the year 2013, consisting of 454,680 invention patents, 396,635 utility model patents, and 273,406 industrial design patents. Table A.1 lists summary statistics for our merged sample.

Table A1: Summary Statistics for Merged Sample

	Merged Sample					**NBS Annual Data on Patent App.**
Year	No of Firms	% of SOE	No. of Patentee	% of SOE	Patent Application	
	(1)	(2)	(3)	(4)	(5)	(6)
1998	60,664	34%	1,244	45%	5,339	6,317
1999	70,576	32%	1,704	41%	8,642	7,884
2000	81,685	30%	2,282	41%	11,549	11,819
2001	98,788	25%	2,901	36%	16,270	15,339
2002	120,631	22%	4,267	34%	26,928	21,297
2003	149,276	20%	5,568	32%	38,574	31,382
2004	229,644	16%	6,826	27%	47,746	42,318
2005	217,636	16%	7,373	27%	63,719	55,271
2006	209,084	17%	8,460	27%	74,653	69,009
2007	194,716	15%	9,022	24%	86,109	95,905
2008	173,310	9%	10,315	18%	103,135	122,076
2009	150,578	11%	9,076	19%	107,480	166,762
2010	125,827	13%	6,320	22%	82,351	198,890
2011	95,345	16%	7,723	26%	137,432	265,612
2012	96,081	16%	7,847	27%	157,287	327,116
2013	93,470	16%	7,548	27%	154,264	359,791

Columns (1) and (3) list the number of firms in our sample and number of patentees per year (we define a firm as a patentee if it has applied once during that year). Columns (2) and (4) show the percentage of state-owned firms (SOE) in our sample and those that are patentees. Following Song and Hsieh (2015), SOEs are defined as firms either registered as SOEs, or their controlling shareholders are state government. The percentage of SOEs is decreasing through the years by privatization. Still, SOEs are more likely to file patents than private-owned enterprises. To assess the quality of the matched sample, we compare the number of the patent application at the aggregate level. Column (5) lists the aggregated number of patent applications in the merged sample and column (6) shows the annual patent applications by medium-to-large firms reported by NBS's China Statistical Yearbook. The number is close before the year 2010. The number of patents and firms drop considerably after 2010, as AMS readjusted its survey sample. However, the trend of patent applications was stable. This suggests the merged sample is representative in terms of capturing the trend of the patent application by medium-to-large firms.

Table 2 shows significant heterogeneity of innovation activity and shares across 2-digit industries. Column (1) lists the average number of firms across 22 industries in each year. Columns (2) and (3) report the average percent of patentees (we define a firm as a patentee if it applied at least once during the sample year 2003 to 2011) and the average percent of state-owned firms in each industry across our sample. Column (4) shows the average percent of state-owned firms that patent in each industry across our sample. In almost all industries, state-owned firms are more likely to become patentees. Columns (5) and (6) show the average granted patent application (includes invention patents, utility model patents, and industrial design) and granted invention patents per patentee in each industry over the sample period. Column (7) is the innovation efficiency defined by equation (4) in text in 2007 in each industry. Column (8) shows the average citations (industry and year adjusted) per invention patent.

Table A2: Summary Statistics for Innovation Activity and Quality across industries

		Average Across Year				Firm Average			
		No. firms	**% patentee**	**% SOE**	**%SOE in Patentee**	**Patents Per pat**	**Invention per pat**	**Innovation Efficiency**	**Patent Quality**
	Industry	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	Food processing	6392	11.50%	17.30%	21.10%	5.30	2.76	0.841	1.575
2	Beverage, Tobacco	1343	26.30%	29.60%	40.50%	6.14	2.91	0.376	1.585
3	Textile	7853	5.90%	7.20%	20.20%	12.73	2.81	0.669	1.689
4	Clothes	2886	4.10%	5.50%	11.70%	14.08	3.63	0.615	1.698
5	Wood, bamboo	1535	6.70%	7.50%	15.20%	8.38	2.49	0.641	1.603
6	Furniture	823	15.00%	6.20%	6.90%	12.86	2.26	0.635	1.391
7	Papers	2365	5.70%	7.90%	20.70%	4.94	3.32	0.72	1.635
8	Printing and record	1537	7.00%	28.80%	29.40%	4.45	2.40	0.707	1.375
9	Culture, educ. Sports	837	18.50%	6.40%	9.20%	9.72	2.65	2.548	1.27
10	Petroleum, coking, nuclear	611	12.80%	22.60%	56.30%	5.92	5.71	2.52	1.542
11	Chemical	6405	19.50%	16.90%	25.70%	4.65	3.64	3.332	1.472
12	Pharmaceutical	1642	47.50%	30.30%	38.40%	4.65	3.61	0.7	1.611
13	Chemical fiber	535	12.60%	10.90%	32.70%	8.42	5.29	0.694	1.908
14	plastic and rubber	4380	14.20%	8.40%	16.10%	4.96	2.63	0.49	1.483
15	Non-metallic mineral	7549	8.10%	15.70%	24.40%	5.71	2.84	1.526	1.503
16	Metal melting, metal	8182	13.70%	10.70%	23.50%	8.65	5.36	4.036	1.661
17	general and special equipment	10525	28.40%	14.40%	22.10%	5.75	3.23	3.514	1.481
18	Automobile,	3545	27.50%	20.00%	33.90%	10.20	5.50	2.278	1.774
19	Railway, ship, aerospace	4909	30.90%	11.50%	15.70%	9.12	5.84	2.531	1.59
20	Electrical machinery	1532	42.00%	24.40%	32.60%	15.16	18.33	1.08	1.509
21	ICT	2319	25.70%	12.20%	21.50%	7.09	3.17	0.843	1.511