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What Drives China's Growth? Evidence from Micro-level Data*

Tomoyuki Iida,[†] Kanako Shoji,[‡] and Shunichi Yoneyama[§]

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Abstract

This paper discusses the sustainability of China's rapid growth mainly based on the estimation of the corporate-level total factor productivity of Chinese listed firms. Since the 1980s, both capital accumulation and rapid technological progress -- measured as total factor productivity (TFP) -- have contributed to the high growth of the Chinese aggregate output. Should the prediction of the standard growth theory be correct, however, economic growth led by capital accumulation is not likely to be long lasting, hence we mainly focus on firm level TFP growth. As a result, we identify four channels that would continue to promote the TFP growth of the Chinese corporate sector at an aggregate level: (i) declining proportion of low-productivity state-owned enterprises, (ii) continuous influx of highly competent new start-ups, (iii) broad catching up trend among the laggards in the firm distribution, and (iv) innovation spawning R&D activities. These four channels would underpin the medium-term economic growth of the Chinese economy.

JEL Classification: N15, O30, O47

Keywords: China, Total Factor Productivity, Catching up, R&D

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1. Introduction

This paper assesses the productivity of the Chinese corporate sector to gauge the sustainability of economic growth in China. As shown in Figure 1(1), the Chinese economy grew rapidly at higher than 10 percent annually on average from the 1990s to the global financial crisis. Although the growth rate has declined to the single digit level since the crisis, the Chinese economy is still leading the world economy, growing at a higher rate than that of the world economy.¹ The growth prospect of the Chinese economy has significant implications for the global economy.

Until recently, economic growth in China had been driven by fast growing TFP and capital accumulation. Zhu (2012) and Liu (2015) argue that the average annual growth rate of the TFP in China from 1978, when the reform and opening-up commenced, to the recent financial crisis was around 3 to 4 percent. In addition, as Figure 1(2) shows, the Chinese saving rate, which has been higher than that of Japan and Korea even during their high-growth period, has supported large-scale investment by the corporate sector. Besides, after the financial crisis, the Chinese government made bold efforts to spur the economy by deploying the so-called four trillion yuan stimulus package, that is, large-scale growth-promoting infrastructure projects.

However, in the long-run, we cannot expect ever-increasing contribution to economic growth from capital accumulation. Solow (1956) suggests that economic growth led by capital accumulation cannot be sustained on a long-term basis without continuous increase in the saving rate.² In fact, investment driven economic growth ended after the leveling-off of the saving rate in both Japan and Korea, which had experienced high economic growth driven mainly by capital accumulation. Then, in China, high economic growth supported by fast growing capital accumulation cannot be sustained for a long period. In this regard, two reasons can be pointed out. First, the saving rate in China is likely to decline in the future since China is on the way to becoming an aging society. Second, as shown in Figure 1(3), the actual growth rate of investment has been declining since around 2012, particularly in the corporate sector, which has been

¹ According to the April 2018 World Economic Outlook by the IMF, the growth rate of the world economy in 2017 was +3.8% while that of the Chinese economy was +6.9%. Using the PPP weight of China in the world economy, 18.2%, we can calculate the contribution of China in 2017 as +1.3%, which means that China accounted for one-third of the world's economic growth.

² Supposing international capital movement is completely free, we cannot claim that an increase in the domestic saving rate always results in domestic capital accumulation. However, as shown in Feldstein and Horioka (1979), because of barriers for international capital movement in reality, an increase in the domestic saving rate strongly correlates with capital accumulation.

suffering from yet-to-divest excess capacity and debt overhang problems. Thus, the sustainability of the economic growth in China depends on the trend of TFP growth.

This paper provides insights into the TFP growth in China to examine the sustainability of the country's economic growth based on facts and empirical analysis using data of listed firms. One of the advantages of using micro data is that we can specifically analyze channels that contribute to TFP growth by making use of the information about heterogeneity across firms, which we cannot observe in aggregate data. Jumping to the conclusion, we found that the following four main channels facilitate the TFP growth in China:

- (i) Declining proportion of low-productivity state-owned enterprises
- (ii) Continuous influx of highly competent new start-ups
- (iii) Broad catching up trend among the laggards in the firm distribution
- (iv) Innovation spawning R&D activities

Assuming that these channels remain functioning, we can expect that the TFP growth will continue to advance, which will promote sustainable growth in China.

The rest of the paper is organized as follows. Chapter 2 calculates TFP measures using data on listed firms and describes the characteristics of the distribution. Chapter 3 assesses the composition effects, where high TFP firms replace low TFP ones, on the aggregate TFP level. Chapter 4 provides facts on the channels for the TFP growth of individual firms. Chapter 5 sets forth our conclusion.

2. Firm Level TFP and the Distribution

Initially, we construct an index of TFP for individual firms. Since we cannot observe TFP levels directly, differently from capital or labor inputs, we assume a Cobb-Douglas production function for individual firms and calculate TFP as Solow residual, following existing literature. We assume that a firm inputs both capital and labor to produce value added, as follows.

$$Y_{it} = A_{it}K_{it}^{1-\alpha}L_{it}^{\alpha}$$

i and t show indexes for firm and time. Y_{it} , A_{it} , K_{it} , L_{it} , and α indicate value added, TFP, capital input, labor input, and cost share of labor, respectively. We can rewrite the

equation and describe A_{it} as follows.

$$A_{it} = Y_{it}/(K_{it}^{1-\alpha}L_{it}^{\alpha})$$

Since all the variables on the right hand side of the equation, including the labor cost share, are observable, we use the equation and calculate firm level TFP.³ We employ annual panel data from 2010 to 2016 of 4,452 Chinese firms listed on the Shanghai, Shenzhen, Hong Kong, and U.S. stock exchanges.⁴ We construct each variable on the right hand side of the equation as follows. We calculate the value added as the sum of operating profit, labor cost, and depreciation, and then deflate using the GDP deflator for each industry.⁵ The total value added of 3,518 firms in 2016, whose value added we can calculate through this procedure, amounts to 7.6 trillion yuan, which corresponds to one-tenth of the Chinese real GDP in 2016. We employ the outstanding amount of tangible fixed assets as capital input while we use the number of employees as labor input. We employ the industrial average of the proportion of labor cost, which we calculate from the proportion of labor cost in value added for individual firms, as the labor cost share.⁶

Next, we note the characteristics of the distribution of the TFP level for individual firms calculated as above. Figure 2(1) shows a histogram of the TFP level. As the distribution is biased toward the right with a skewness of 3.79, the difference between the TFP level of a standard firm and that of a high TFP level firm is large. To see this point numerically, we define "frontier firms" as firms with a TFP level in the top ten-percentile for each sector, and we find that the median TFP level of frontier firms is

³ Since we do not take into account neither the utilization of inputs nor scale economics in calculating TFP, our TFP may include the effect of macroeconomic factors. Moreover, we do not standardize the TFP of individual firms by subtracting their sector average as in Aw et al. (2001). This is because, as we show in Chapter 3, not only sector specific factors but also ownership, firm age, and so on will affect firm level TFP, and one of our objectives is to identify these factors clearly. In addition, it is possible that our analysis has so-called survival bias because we employ data on listed firms. However, as an extremely small number of firms were delisted during the sample period, the effect of the bias on our analysis will be very small.

⁴ In chapter 4, we use $\ln A_{it} - \ln A_{it-1}$ as the TFP growth for each firm. We exclude firms with extremely high or low TFP growth, that is, those with TFP growth in the top and bottom one percentiles. Moreover, we exclude firms who lack at least one of the data items to calculate TFP level as below.

⁵ In addition to our method to calculate value added (the additive method), another method will be using revenue excluding sales administrative expenses (the subtractive method). The correlation between the pooled sample of value added derived from the former method and that derived from the latter method is 0.95. This paper employs the additive method because we can have a larger sample. Meanwhile, since sector specific GDP deflators are not available in China, we alternatively calculate the growth by subtracting real GDP growth from nominal GDP growth for each sector.

⁶ In calculating the average proportion of labor cost for each sector, we exclude firms with a proportion higher than one as outliers.

2.7 times higher than that of the entire sample as shown in Figure 2(2). It suggests that, supposing that the TFP level of frontier firms is fixed at the current level and that the TFP of a standard firm with the entire sample's median TFP level grows at an annual rate of 5 percent, the gap is so large that it takes more than 20 years for the standard firm to reach the frontier. Thus, since there is a large gap in the TFP level between standard Chinese firms and frontier firms, potentially the aggregate TFP can grow through standard firms' catching up to the frontier.⁷

3. TFP Growth through Composition Effect

This chapter shows the characteristics of firms with a high TFP level and those with a low TFP level and examines how the compositional change affects the aggregate TFP level (Composition Effect). In China, since the 2000s, in the course of the transition from a planned economy to a market economy, the presence of SOEs, whose TFP level generally seems to be low, has declined while new private firms have commenced business one after another, some of whom have international competitiveness. We focus on the effect of this sort of acceleration in the firms' turnovers on the aggregate TFP level through the composition effect and evaluate it using the firm level TFP data, which we derived in the previous chapter.

3.1 Declining Presence of Low-Productivity SOEs

Since the 2000s, a number of structural changes have occurred in the Chinese economy, and one of the symbolic changes is the declining presence of SOEs. Figure 3 shows the asset proportion of SOEs in the industrial sector. The proportion was higher than 50% in the early 2000s, but it has declined to just over 10% recently.⁸

Several studies have pointed out the inefficiency of SOEs in various aspects. First, SOEs have a strong relationship with the Chinese government and play an important role in achieving the government's objectives such as economic growth and employment stability. Thus, if required by the government, they invest and employ a lot without regard to commercial concerns, and, as a result, their management tends to be

⁷ Nakamura et al. (2018) point out that the variance of the TFP level of Japanese listed firms is smaller compared to that of U.S. listed firms and evaluate that there are few firms who strongly lead the TFP of the entire economy while there are few firms with an extremely low TFP level.

⁸ Although data on the proportion of SOEs in the non-industrial sector is not available, the proportion will be higher than that of the industrial sector because there exist many SOEs in some sectors such as banking and public services.

inefficient. Second, to support SOEs who play these important roles, the government and financial institutions provide them with a variety of preferential treatment. Some studies point out that the government supports SOEs by the exemption of dividends, and that financial institutions provide them with a favorable financing environment because they have implicit government guarantees.⁹ Due to such preferential treatment, the SOEs can stay in the market even if their profitability is so low that they should be required to exit. As a result, the TFP level of the SOEs is generally considered to be low. Table 1(1) shows the regression result of the individual TFP level, which we derived in the previous chapter, on SOE dummy, which takes 1 if a firm is a SOE and 0 otherwise, and says that the TFP level of SOEs is lower than that of private firms by 17 percentage points on average.¹⁰

It is often pointed out in literature that the existence of low-TFP SOEs has worsened the economy-wide resource allocation in China.¹¹ In this respect, the continuous decline in the relative scale of SOEs has contributed to raising the aggregate TFP level through the composition effect. To be specific, based on the above estimation result, we can calculate that the decline in the proportion of SOEs, who have a lower TFP level than that of private firms by 17 percent, from 72.7 percent in 2001 to 12.8 percent in 2017, has contributed to economy-wide TFP growth by 0.7 percent points annually.¹²

3.2 Increase in High-Productivity New Firms

While the presence of SOEs has declined, a number of private firms have actively commenced business in China, and the turnover has accelerated. Figure 4 shows the

⁹ The European Union Chamber of Commerce in China (2016) points out that one form of preferential treatment provided by the government to the SOEs is the exemption of dividends. There are at least two sorts of preferential treatment provided by financial institutions. Song and Xiong (2018) claim that financial institutions provide credit to the SOEs under favorable terms compared to private firms since the SOEs are assumed to constitute part of the government and banks can expect implicit guarantees from the government if their business status deteriorates. In addition, the IMF (2016b) claims the SOEs raise funds with favorable loan rates by making good use of land, given by the government, as collateral.

¹⁰ Hsieh and Klenow (2009) show that the TFP level of SOEs is lower than that of private firms by around 40% while Dollar and Wei (2007) show that the capital productivity of SOEs is lower than that of private firms by around 50%.

¹¹ Hsieh and Klenow (2009) claim that resource misallocation has pushed down the aggregate TFP level in China because of the existence of SOEs. Dollar and Wei (2007) point out that one of the factors that have worsened the economy-wide capital efficiency is the fact that SOEs, who have relatively low capital efficiency, depend on bank loans more than private firms, who have better capital efficiency.

¹² The calculation here could be somewhat overestimated. To be precise, the proportion of SOEs used here is confined to the industrial sector due to data limitation, but the decline in the proportion of SOEs could be smaller in the non-industrial sector.

distribution of the firm age of listed firms in China, the U.S., and Japan. The proportion of firms younger than 20 years old in China is higher than that of the U.S. and Japan, and the proportion of firms younger than 10 years old is smaller than that of the U.S., but far larger than that of Japan.

In addition, another characteristic of China is that there are many internationally competitive firms among newly established ones. Table 2 shows the average firm age by country/region of listed firms who ranked in the world's top 1,000 for market capitalization. In 2016, 91 Chinese firms ranked in the world's top 1,000, and their average firm age, 22 years old, is younger than that of any other country. Moreover, the competitiveness of newly established Chinese firms is also apparent in their TFP level. Table 1(2) shows the regression result of the individual TFP level of our data on firm age, and it indicates that, if a firm is 10 years younger, it tends to have a 10 percent higher TFP level. In addition, considering the fact that many newly established firms are private firms, we show another regression result in table 1(3) by adding an SOE dummy in explanatory variables and get similar results.

Thus, we argue that the continuous influx of high-TFP newly established firms has contributed to the increase in the aggregate TFP level through composition effect.

One of the reasons why the TFP level of newly established firms is relatively high may be that the entry conditions for emerging companies are tightening due to the existence of SOEs with a TFP level that is so low they should exit from the market.¹³ Usually, if entry conditions tighten, the influx of start-ups will decrease. However, even in these circumstances, the fact that high-TFP newly established firms are continuously entering the market is a big advantage for the Chinese economy. This can occur because the Chinese authorities have actively engaged in incubation.¹⁴

4. TFP Growth of Individual Firms

This chapter assesses factors that affect the TFP growth of incumbent companies in China. Existing literature has emphasized mainly two channels: growth by catching up,

¹³ Caballero et al. (2008) claim that the existence of zombie firms, which should have exited from the market, worsens the profitability of healthy firms, and the TFP level required for newcomers increases. As the IMF (2016a) points out, the number of firms who have extremely low profitability but stay in the market is considered to be increasing.

¹⁴ The Chinese authorities have introduced some exemptions for emerging companies, such as the reduction of corporate tax by half and a substantial exemption from value added tax.

where low TFP firms get technology spillover by imitating high TFP firms, and growth by their own innovations. We start by summarizing the discussions in existing literature on firm level TFP growth and then quantitatively evaluate which channels are important for the TFP growth of Chinese firms using our panel data set.

4.1 Growth by Catching Up

A low TFP firm catches up to high-TFP frontier firms through technology spillover by imitation.¹⁵ Coe and Helpman (1995) and Coe et al. (1997) empirically show that foreign technology transfers to domestic firms by their imitation of the superior technology of foreign firms through trading activities. Furthermore, Branstetter (2001) compares the spillover effect from domestic firms and that from foreign firms and points out that the former effect is more important. Also, Fukao et al. (2011) show that low TFP firms tend to catch up to domestic frontier firms, who have a high TFP level, but the pace of catching up to world frontier firms, who have an even higher TFP level, is slower than that to the domestic frontier. Thus, among the literature on growth by catching up, some claim that domestic frontier firms are more important than foreign frontier firms as targets to catch up to.

4.2 Growth by Innovations

While low TFP firms can grow through catching up, high TFP firms have less room to catch up, and they are required to grow through their own innovations (Acemoglu et al. 2006). Aoki et al. (2017) argue that one of the causes of low productivity growth in Japan is that Japanese firms could not transition smoothly from growth by catching up through imitating the technology of U.S. firms to growth by their own innovations. These studies above have implications for the sustainability of future economic growth in China. That is, if China continues to grow to a higher development stage, its own innovations will become more important. Indeed, it is pointed out that R&D investment in China has been active since the 2000s (Fan 2018). Figure 5 shows a positive correlation between R&D expenditure and nominal GDP per capita by country. China's R&D expenditure is relatively active compared with its mediocrity in per capita GDP. In addition, some Chinese firms conduct R&D activities to acquire technology that has yet to be established even by firms in advanced economies. For example,

¹⁵ Here, the term spillover effect refers to, in precise terms, the externality to acquire the results of R&D activities by other firms through reverse engineering of traded goods and interactions between engineers.

representative Chinese firms in the information technology sector undertake R&D investment actively for the practical use of Artificial Intelligence and Virtual Reality.

4.3 Empirical Analysis

In this section, we empirically analyze the determinants of TFP growth for listed firms in China based on the discussions in existing literature introduced in the previous section. We use annual firm-level panel data from 2011 to 2016, and Table 3 shows the descriptive statistics.

To begin with, we estimate the following equation.

$$\begin{aligned} \Delta \ln A_{ijt} = & \alpha_1 + \alpha_2 \ln \text{Export}_{ijt-1} + \alpha_3 \ln \left(\frac{A_{jt-1}^F}{A_{ijt-1}} \right) + \alpha_4 \ln R\&D_{ijt-1} \\ & + \alpha_5 \ln \text{Sale}_{ijt-1} + \sum_j \iota_j I_dum_j + \sum_t \tau_t T_dum_t \end{aligned}$$

The subscripts, i , j , and t , represent firm, sector, and time, respectively. Export_{ijt} shows export sales and is a proxy for trade activities. Some point out the importance of reverse engineering of imported goods in technology spillover from foreign firms to Chinese ones. To capture this kind of effect, it is conceivable that we should use import related data as an explanatory variable rather than export sales.¹⁶ However, we use export sales due to data limitation. If there exists an effect of catching up to foreign firms through exporting activities, α_2 will be positive. A_{jt}^F is the average TFP level of domestic frontier firms in China, and A_{jt}^F/A_{ijt} represents the distance of the TFP level of each firm to the frontier. If firms catch up to the domestic frontier, α_3 will be positive. $R\&D_{ijt}$ shows R&D expenditure by each firm. If R&D expenditure for its own innovations results in TFP growth, α_4 will be positive. In addition, to control firm size, sectoral characteristics, and time specific aggregate shocks, we add sales Sale_{ijt} , sectoral dummies I_dum_j , and time dummies T_dum_t as explanatory variables.

Table 4(1) shows the estimation result of the equation. The effect of catching up to the domestic frontier and that of R&D activities on TFP growth are statically significant. In contrast, firms with larger export sales do not necessarily increase TFP growth, and based on this estimation result, we cannot confirm the existence of the effect of catching up to foreign firms through trading activities.

¹⁶ Keller (2004) surveys the channels of international technology spillover and argues that the channel through importing is important while the channel through exporting is relatively minor.

We can summarize the implications as follows.

- (i) Low TFP firms tend to catch up to domestic frontier firms.
- (ii) R&D activities increase TFP growth.
- (iii) We have no significant result for the effect of technology spillover from foreign firms in the sense that firms with larger export sales tend to have higher TFP growth.

4.4 Robustness Check

This section assesses the robustness of our baseline estimation results in the previous section.

First, we evaluate the robustness of our specification. Table 4(2) shows the estimation result of the fixed effect model, adding firm specific dummies to the baseline specification, while Table 4(3) shows the estimation result for the random effect model. They show that the sign and significance of all major elasticity, α_2 , α_3 and α_4 , do not change a lot. Meanwhile, the result of a Hausman test shows that we should employ the fixed effect model rather than the random effect model.

Second, we evaluate the robustness of our dataset. In the previous section, we excluded firms with TFP growth in the top and bottom one percentiles for each year. In this section, we use the entire sample and test whether we have any meaningful difference in our estimation results. Moreover, we exclude export sales, whose coefficient is not significant in our baseline estimation, and test our results with a much larger sample. Table 4(4) and 4(5) show the results. We can find that there is no meaningful difference in the sign and the significance for major elasticity.

In light of these points, our estimation results are robust.

5. Conclusion

This paper discusses the sources of TFP growth in China using data on listed firms to gauge the sustainability of Chinese economic growth. In particular, we evaluate composition effect, where high TFP firms replace low TFP ones, on the aggregate TFP and the factors that affect the TFP growth of individual firms.

We showed that as a typical example of the composition effect, since the 2000s the proportion of low-productivity SOEs has continuously declined, while high-productivity firms have actively entered the market. The Chinese government indicates a policy to push forward the shakeout of unprofitable SOEs, though the government previously was not so proactive in this regard.¹⁷ Moreover, the Chinese government has implemented and expanded a massive tax reduction for venture companies. These policies will contribute to improving the aggregate TFP through accelerating the exit and entry of firms in the Chinese economy.

In addition, although we could not confirm that technology spillover from foreign firms is a factor that affects the TFP growth of individual firms, partly due to data limitation, we confirmed that both the effect of catching up to domestic frontier firms and the effect of R&D activities are important in terms of TFP growth. As we showed in chapter 2, there still exists a large productivity gap between frontier firms and other listed firms. Thus, the effect of catching up to the frontier will continue to be effective. Moreover, some firms engage in active R&D activities to acquire new technology that has yet to be established even by firms in advanced economies. As the Chinese government is providing preferential treatment to support the R&D activities of such firms, the effect of innovations through R&D activities will likely remain functioning.¹⁸

The Chinese economy has been growing by around 7 percent annually. The trend of TFP growth is an important issue to consider the sustainability thereof. The focus of this study is confined to listed firms in China, but at least based on the analysis, the Chinese aggregate TFP has increased through the following four channels: (i) declining proportion of low-productivity state-owned enterprises, (ii) continuous influx of highly competent new start-ups, (iii) broad catching up trend among the laggards in the firm distribution, and (iv) innovation spawning R&D activities. Assuming that these channels continue to be effective, the Chinese economy is likely to maintain its current growth momentum.¹⁹

¹⁷ The government activity report at National People's Congress in 2016 shows a policy to promote SOE reforms as one of the government's supply side reforms. In response to this, at the executive meeting of the State Council in May 2016, they proposed some concrete measures such as the disposal of 345 unprofitable SOEs.

¹⁸ In China, one form of preferential treatment is that the government cut the corporate income tax rate from 25% to 15% for firms who are recognized as "high tech firms intensively supported by the nation" if they meet certain conditions, such as with respect to the R&D expenditure to revenue ratio.

¹⁹ One of the risks that worsen the turnover of Chinese firms is the decline in the financial intermediary function due to the escalation of the debt-overhang problem mainly in the corporate

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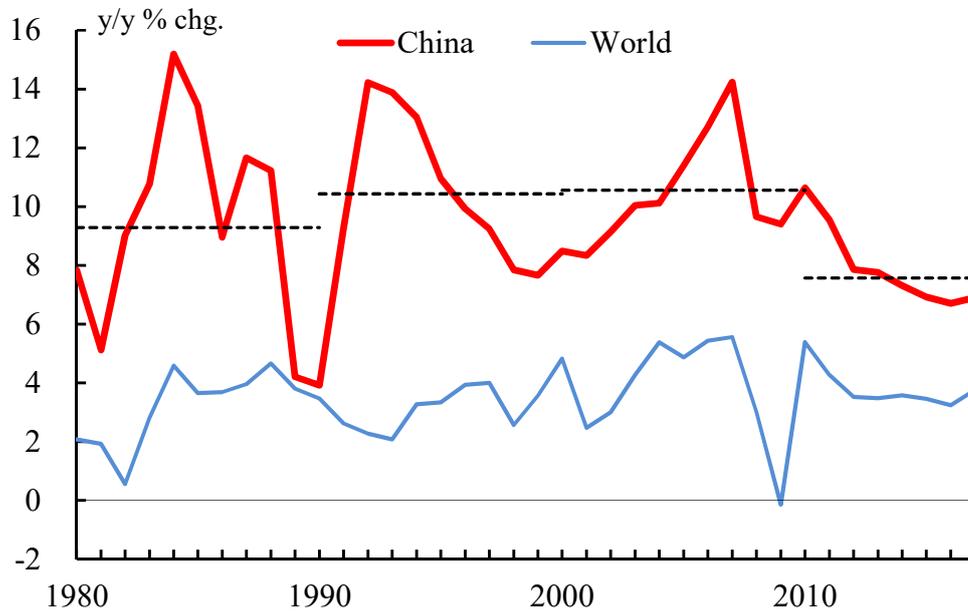
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sector. Moreover, today, one of the risks that impede R&D activities by Chinese firms is the request from the U.S. government to discontinue providing subsidies to the high-tech industry to promote the plan, "Made in China 2025."

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Figure 1: Macroeconomic indicators in China

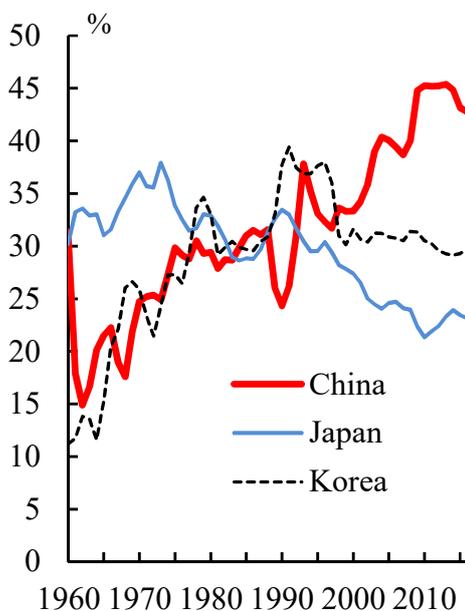
(1) GDP growth



Notes: The latest data are as of 2017. The dashed lines indicate the average growth rate during 1980s, 1990s, 2000s and 2010-2017, respectively in order from the left.

Sources: CEIC, IMF

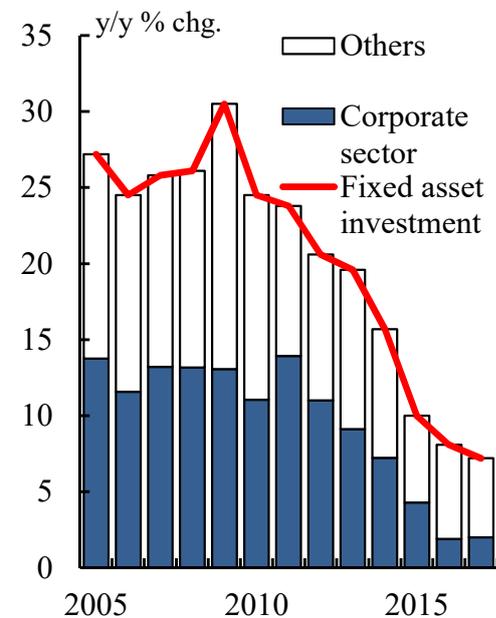
(2) Saving ratio



Note: Nominal GFCF/ nominal GDP. The latest data are as of 2016.

Source: HAVER

(3) Fixed asset investment

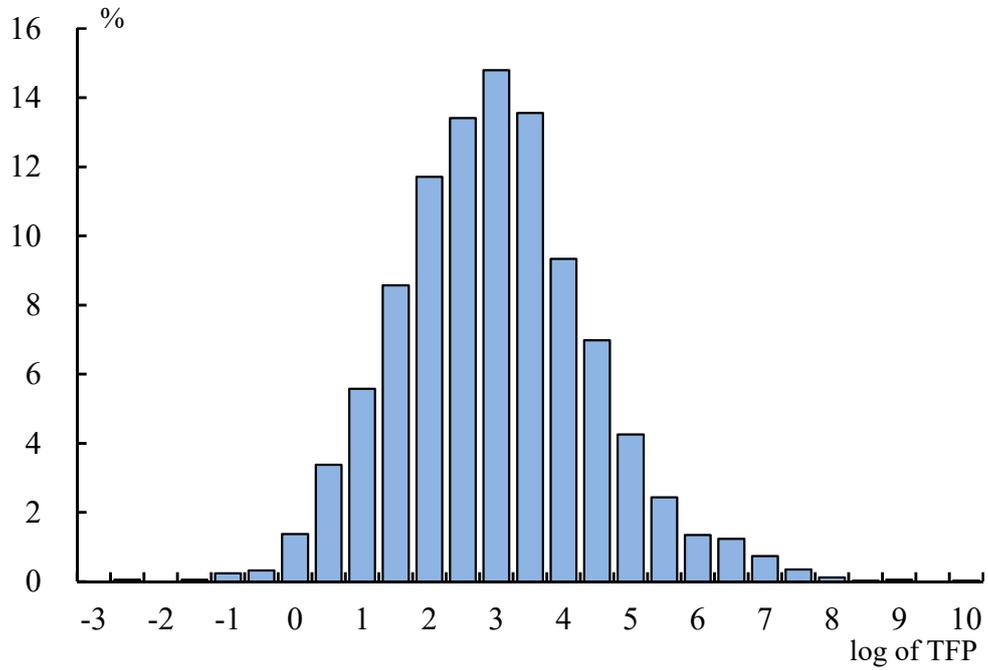


Note: Corporate sector shows the sum of manufacturing and service.

Sources: CEIC, IMF

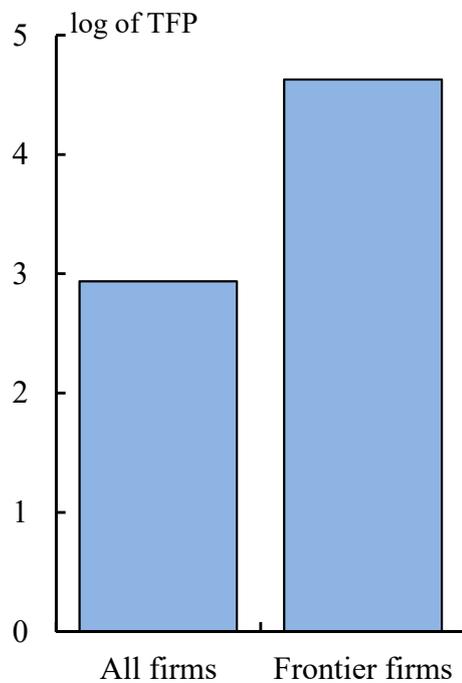
Figure 2: TFP level of listed firms

(1) Distribution of TFP level



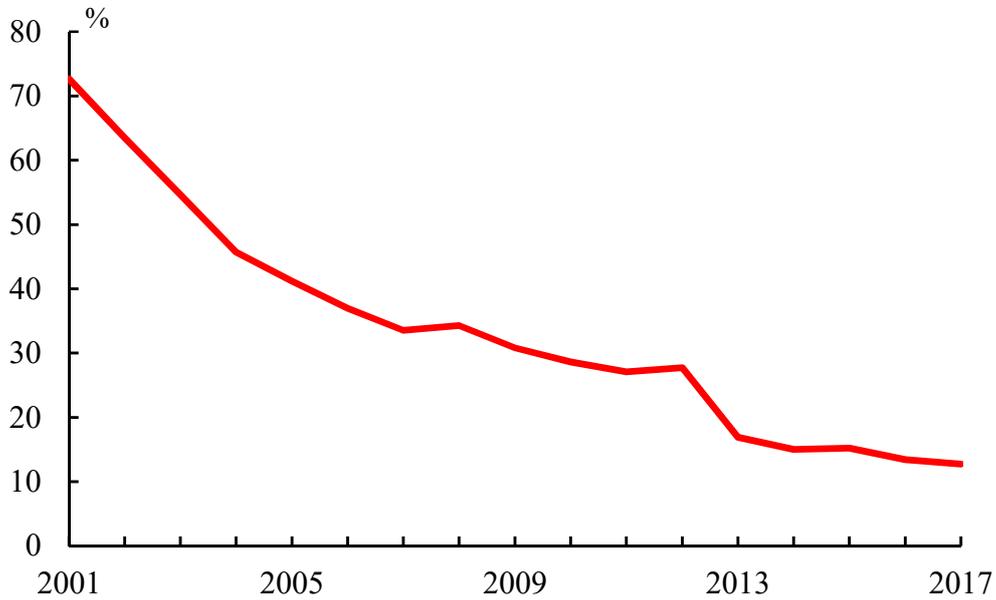
Note: The TFP level of 3,407 firms is available for 2016.

(2) TFP level of all listed firms and frontier firms



Note: The data are as of 2016. The median of each group.

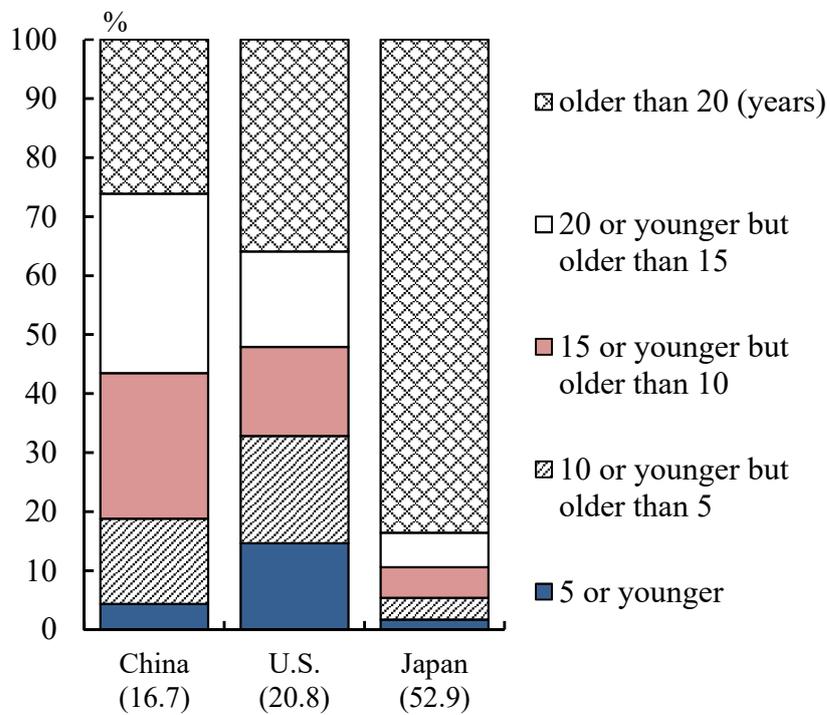
Figure 3: Proportion of SOEs in industrial sector



Note: The proportion is in terms of total asset.

Source: CEIC

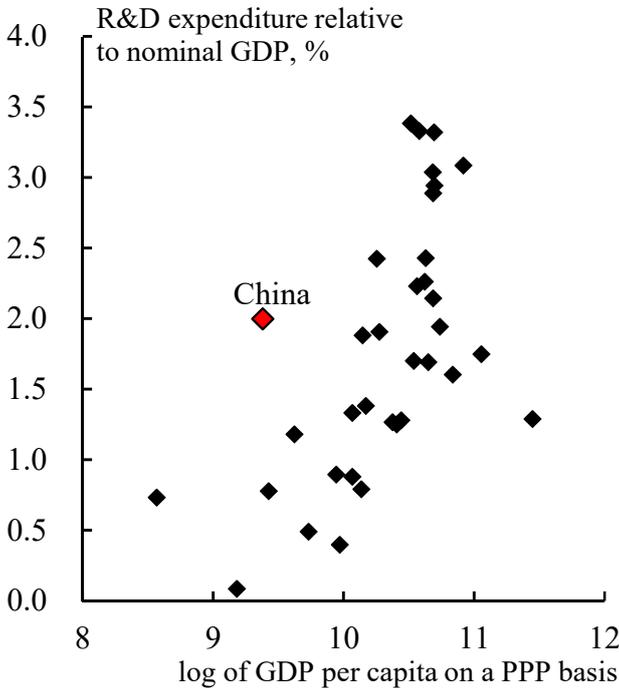
Figure 4: Age of listed firms



Note: The data are as of 2016. Average age in parentheses.

Source: Bloomberg

Figure 5: R&D expenditure by country



Note: The data are the average of 2011, 2013, and 2015.
Sources: IMF, OECD

Table 1: TFP level and firms' characteristics

	Dependent variable: TFP level		
	(1) b/se	(2) b/se	(3) b/se
SOE dummy	-0.17*** [0.03]		-0.13*** [0.03]
Firm age		-0.01*** [0.00]	-0.01*** [0.00]
Time dummy	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes
N	19,209	18,520	18,520
R ²	0.600	0.610	0.610

Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% respectively. Standard errors are in parentheses.

Table 2: World's top 1,000 firms by country/region

	Country/Region	Number of firms	Average firm age
1	U.S.	363	34
2	China	91	22
3	Japan	84	59
4	U.K.	48	36
5	France	41	41
6	Germany	34	29
7	Switzerland	25	41
8	Canada	34	37
9	Hong Kong	28	31
10	Australia	20	29

Notes: The table shows firms whose market capitalization was in the world's top 1,000 in 2016.

The country/region is in order of the total value of market capitalization.

Source: Bloomberg

Table 3: Summary statistics

	N	Mean	sd	Min	Max
TFP growth rate (dln)	14,790	-0.04	0.47	-2.31	2.29
Export sales (ln)	8,158	18.71	2.37	4.62	25.10
Distance to frontier (dln)	19,209	1.69	1.02	-5.34	9.24
R&D expenditure (ln)	18,372	17.10	1.68	6.04	23.59
Sales (ln)	27,117	20.97	1.66	7.60	28.67

Table 4: Estimation results

Independent variables	Coef.	Dependent variable: TFP growth				
		(1)	(2)	(3)	(4)	(5)
		OLS	Fixed effects	Random effects	OLS	OLS
		b/se	b/se	b/se	b/se	b/se
Constant	α_1	-0.496* [0.264]	-2.645*** [0.680]	-0.725** [0.290]	-0.494* [0.282]	-0.481*** [0.097]
Export	α_2	-0.002 [0.004]	-0.005 [0.009]	-0.004 [0.004]	-0.004 [0.004]	
Distance to frontier	α_3	0.158*** [0.008]	0.698*** [0.021]	0.203*** [0.009]	0.217*** [0.010]	0.138*** [0.005]
R&D Expenditure	α_4	0.017** [0.007]	0.026* [0.014]	0.018** [0.007]	0.016* [0.008]	0.008** [0.004]
Sales	α_5	-0.019*** [0.007]	0.053 [0.033]	-0.022*** [0.008]	-0.021** [0.009]	-0.004 [0.004]
Time dummy		Yes	Yes	Yes	Yes	Yes
Industry dummy		Yes	—	Yes	Yes	Yes
N		4,162	4,162	4,162	4,244	10,260
r^2		0.116	0.362	—	0.124	0.108

Notes: ***, **, and * denote statistical significance at 1%, 5%, and 10% respectively.
Standard errors are in parentheses.