

# China's Declining Business Dynamism\*

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## Abstract

We document five novel facts about the dynamism of Chinese manufacturing firms between 2003 and 2018. We show that (i) the revenue and capital shares of young firms have declined, (ii) life cycle growth of firm revenues and assets has declined, (iii) life cycle growth of process efficiency / product quality and investment in intangibles has declined (iv) younger firms have higher capital productivity than older firms, with the gap increasing over time, (v) the dispersion of capital growth and the responsiveness of capital growth to capital productivity have both declined. Using a simple model, we estimate that the lower life-cycle productivity growth of young firms reduces manufacturing productivity growth by 0.8 percentage points annually, and worsening allocative efficiency of capital between young and old firms reduced manufacturing TFP by 1.25 percent between the early 2000s and late 2010s. We find that business dynamism is weaker in provinces where state-owned enterprises (SOEs) account for a larger share of the capital stock.

**Keywords:** China, aggregate productivity, growth, business dynamism.

**JEL codes:** O11, O47.

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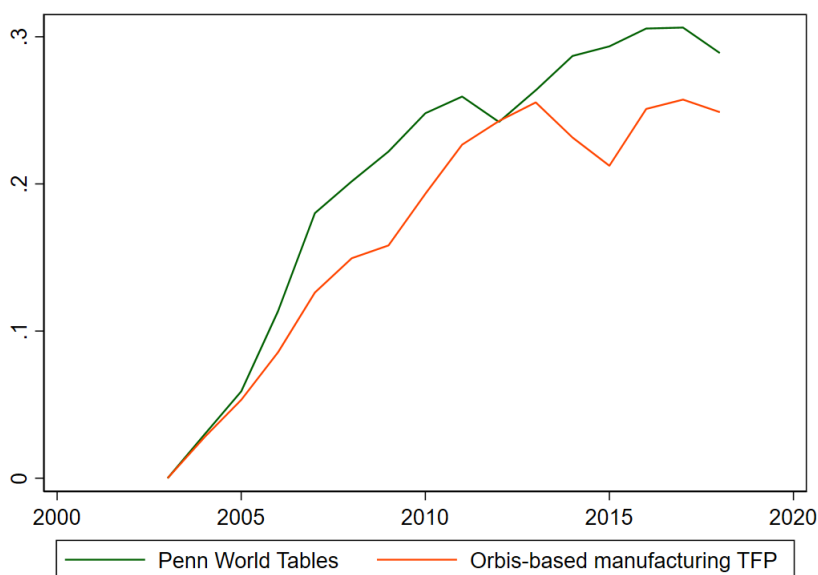
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## 1. Introduction

After extraordinary growth in the 2000s, China's productivity growth has stagnated in the 2010s (Figure 1). While productivity growth has also slowed in other countries (Fernald, Inklaar and Ruzic, 2023), China's productivity deceleration in the post-global financial crisis (GFC) period has been particularly dramatic, with TFP rising by 22 percent between 2003 and 2011 and a mere 5 percent between 2011 and 2019. Previous research has shown that China's growth in the 2000s was largely driven by the rapid growth of young private firms (Brandt, Van Biesebroeck and Zhang, 2012), enabled by reforms of state-owned enterprises (Hsieh and Song, 2015) and WTO access (Brandt, Biesebroeck, Wang and Zhang, 2017). However, a lack of representative firm-level data covering the pre- and post-GFC period has made it difficult to identify the factors explaining the recent productivity slowdown.

Figure 1: Aggregate and Manufacturing Productivity (log-scale)



**Notes:** The figure plots TFP on a log-scale (y-axis in log points) and normalized to 0 in 2003. The green line reports aggregate TFP from the Penn World Tables, while the orange line reports manufacturing TFP constructed from the Orbis database (methodology described in the text).

We fill this gap by using a firm-level panel from Bureau Van Dijk's Orbis database to analyze productivity and firm dynamism trends for China's manufacturing sector from 2003 to 2018.<sup>1</sup> In contrast to the Chinese Industrial Survey (CIS) whose coverage ends

<sup>1</sup>Orbis data has predominantly been used to study productivity and firm dynamics in European coun-

in 2013, Orbis has extensive coverage of manufacturing firms with more than RMB 5 million in revenues from 2003 through 2018. As we show in Figure 1, average manufacturing TFP constructed bottom-up using these Orbis data exhibits a similar trend to aggregate TFP, plateauing in the 2010s.<sup>2</sup>

We use the firm-level data to document five novel facts about Chinese business dynamism between 2003 and 2018. The first fact is that the share of economic activity accounted for by young firms declined substantially over time. The revenue share of firms under 10 years of age fell from around 70% in 2004/5 to around 30% in 2017/8. Through the lens of standard growth models, this implies that the portion of growth attributable to young firms declined over time (Garcia-Macia, Hsieh and Klenow, 2019). The second fact is that life cycle growth of firms declined over time. We measure life-cycle growth as the 3-year growth rate of young firms relative to older firms, similarly to Eslava, Haltiwanger and Pinzón (2022). We find that life-cycle revenue growth fell by half between 2003-2010 and 2011-2018. The third fact is that the life cycle growth of process efficiency / product quality has declined, along with investment in intangibles with age. We follow Hsieh and Klenow (2009) in defining TFPR and TFPQ respectively as revenue productivity (i.e. inclusive of markups) and process efficiency / quality.<sup>3</sup> We do not find substantial changes in how TFPR evolves with age. This suggests that young Chinese firms in the 2010s were investing relatively less in R&D, marketing or customer acquisition. Consistent with this, we document a decline in the life-cycle growth of intangible capital.

The fourth fact is that younger firms have higher capital productivity (revenues over assets) than their older counterparts, with this gap increasing almost by half over time. The existence of large capital productivity gaps across firms is consistent with evidence from Bai, Lu and Tian (2018), who infer the presence of large financial frictions using data on industrial firms between 1998 and 2007. By extending the sampling time frame, we show that, if anything, such frictions have worsened. The fifth fact is that both the dispersion of capital growth and the elasticity of capital growth to capital productivity have declined over time. We estimate this elasticity by regressing firm-level capital growth on capital productivity separately by sub-period. We find that the responsive-

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tries (Gopinath, Kalemli-Özcan, Karabarbounis and Villegas-Sanchez, 2017; Kalemli-Özcan, Sørensen, Villegas-Sanchez, Volosovych and Yesiltas, forthcoming), but this is the first paper of which we are aware to use Orbis specifically for China.

<sup>2</sup>Figure 12 in the Appendix additionally includes service sector firms in Orbis for which data is available from 2014 to 2018.

<sup>3</sup>Because we do not observe firm-level prices, measuring productivity using revenue data can conflate markups with quality and process efficiency (Foster, Haltiwanger and Syverson, 2008). Given an assumed value for the elasticity of demand faced by firms, we can separately recover markups and other 'wedges' (in TFPR), and process efficiency and quality (in TFPQ).

ness of capital growth to capital productivity has declined most for very young and very old firms. These facts suggest that the efficiency of capital reallocation between young and old firms may have worsened over time, contributing to the weakening life cycle growth and potentially also to the slowdown in aggregate productivity. When put together with fact 3 (little change in the life-cycle growth of TFPR over time), facts 4 and 5 indicate that more recent cohorts of firms face both higher and more persistent distortions to their capital stock. Despite facing initially higher distortions than older cohorts (fact 4), the decline in the responsiveness of capital reallocation (fact 5) ensures that implies that TFPR life-cycle dynamics are broadly unchanged (fact 3).

These five facts show that business dynamism has been declining in China. We use a simple model with an exogenous life-cycle to quantify the potential impact of these trends on manufacturing productivity. We find that the decline in the life-cycle dynamism lowers manufacturing TFP growth by 0.8 percentage points per year. Half of this decline stems from a lower share of young firms (who tend to have high growth rates), and half stems from lower TFPQ growth of young firms relative to old firms (holding the share of young firms constant). We estimate that the worsening allocation of capital across age groups lowered TFP by 1.25 percent between the early 2000s and late 2010s, or roughly 0.12 percentage points annually.

Similar declines have also been occurring in other countries (Calvino, Criscuolo and Verlhac, 2020; Akcigit, Chen, Díez, Duval, Engler, Fan, Maggi, Tavares, Schwarz, Shibata and Villegas-Sánchez, 2021), including the U.S. (Decker, Haltiwanger, Jarmin and Miranda, 2016). Explanations for this simultaneous decline in multiple countries include aging populations leading to declines in entrepreneurship (Pugsley and Şahin, 2018), rising adjustment costs (Decker, Haltiwanger, Jarmin and Miranda, 2020), declining knowledge diffusion (Akcigit and Ates., 2019b), increases in anti-competitive behavior by market leaders (Covarrubias, Gutiérrez and Philippon, 2019), and increasing efficiency advantages for large incumbents due to falling overhead costs (Aghion, Bergeaud, Boppart, Klenow and Li, 2023). While it is outside the scope of this paper to evaluate the importance of each of these, we consider a China-specific explanation: transition dynamics following the large-scale reforms of state-owned enterprises during the 2000s. More than 80 percent of SOEs between 1998 and 2007 closed, privatized or merged (Hsieh and Song, 2015), creating new opportunities for private firm growth and leading to an increase in entry rates of new firms (Brandt, Kambourov and Storesletten, 2020a). Since 2007 however, the pace of SOE reform has slowed, with the SOE share of industrial assets remaining at almost 40% in 2019 despite substantially lower capital productivity (Jurzyk and Ruane, 2021). We explore this explanation by correlating our measures of business dynamism with SOE intensity across provinces.

We first use our data to show that SOEs have lower revenue productivity and capital productivity than private firms. This fact has been extensively documented for Chinese industrial firms prior to 2013, including by [Brandt et al. \(2012\)](#); [Hsieh and Song \(2015\)](#); [Bai et al. \(2018\)](#). Our data show that these productivity gaps remain through 2018, including in the service sector, for which we have data post-2013. We then focus on two measures of dynamism: life-cycle growth of firms and the responsiveness of capital growth to capital productivity. We find that state presence, measured by the SOE share of assets in a province, is associated with both weaker life-cycle growth of firms and less responsive capital reallocation among private firms. Our results provide support for the view that China's high business dynamism in the 2000s was catalyzed by SOE reforms, and that the slowdown in the pace of SOE reform ([Rosen, Leutert and Guo, 2018](#)) is contributing to China's slower TFP growth. While it is well established that SOE reform can trigger substantial direct gains through resource reallocation ([Hsieh and Klenow, 2009](#); [Jurzyk and Ruane, 2021](#)), our results provide suggestive evidence of a new indirect mechanism through which SOE reform in China could boost productivity growth – improving business dynamism. We acknowledge however that many other important policy changes occurred in China during the period we consider that may have affected business dynamism but which we do not explore in this paper. These include changes in industrial policy, local government debt and infrastructure investments, increased openness to trade and reductions in frictions to internal migration.

Declining business dynamism has been documented empirically and studied extensively both in the U.S. ([Decker et al., 2016](#); [Akcigit and Ates., 2019a](#); [Pugsley, Sedlacek and Sterk, 2021](#)) and for a larger set of countries ([Calvino et al., 2020](#); [Akcigit et al., 2021](#)). Closely related, [Brandt, Litwack, Mileva, Wang, Zhang and Zhao \(2020b\)](#) document declines in firm-level reallocation in the post-GFC period up to 2013 using China's Industrial Survey (CIS), with a similar decline in productivity and dynamism found in [Brandt, Biesebroeck, Zhang and Wang \(2023\)](#) who additionally correct for mismeasurement in the CIS.<sup>4</sup> We contribute by considering a more extensive time period during which China's productivity growth stalled, as well as considering a wider range of business dynamism measures. A number of papers have explored the importance of business dynamism for aggregate productivity, and therefore economic growth, in the U.S. For example, [Garcia-Macia et al. \(2019\)](#) find that entry of new firms accounts for around a quarter of U.S. productivity growth between 1983 and 2013. [Decker et al. \(2020\)](#) provide evidence that firm responsiveness to shocks has been declining in the U.S. and that this has contributed to slow productivity growth. [Akcigit and Ates. \(2019a,b\)](#) high-

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<sup>4</sup>[Chen, Chen, Hsieh and Song \(2019\)](#) also estimate substantial over-reporting of value-added in the CIS. We discuss potential measurement issues with Orbis in Section 2..

light that declining U.S. business dynamism reflects lower knowledge diffusion between firms. [Akcigit et al. \(2021\)](#) examine the role that market power and M&As play in driving business dynamism in a larger set of countries.

An extensive literature has documented how the various large-scale reforms in the early 2000s spurred China's productivity growth, including entry into the WTO and reductions in external trade barriers ([Brandt et al., 2017](#)), reductions in internal trade and migration barriers ([Tombe and Zhu, 2019](#)), and SOE reform ([Brandt et al., 2012](#)). Studies using rich firm-level data have also documented the importance of the private sector ([Hsieh and Song, 2015](#)), with the entry and rapid growth of young private firms the primary driver of aggregate productivity growth ([Brandt et al., 2012](#)). However, firm-level studies for the years following the 2008 financial crisis show that this dynamism had started losing steam, with lower firm productivity growth and entry during 2008-2013 ([Brandt et al., 2020b](#); [Brandt and Lim, 2020](#)). We contribute to the literature on China's reforms by using new data to show that the dynamism catalyzed by the reforms continued to lose steam until at least 2018, and that state presence is negatively associated with business dynamism.

The rest of the paper is organized as follows. Section 2. describes the Orbis dataset, and shows that it is able to match broad aggregate productivity trends. Section 3. lays out five stylized facts that point to declining business dynamism. Section 4. presents a simple model to quantify the aggregate impacts of the decline in life-cycle productivity growth and worsening capital misallocation. Section 5. discusses the relationship between declining dynamism and state presence. Section 6. concludes.

## 2. Orbis Data

We use firm-level data from Bureau Van Dijk's (BvD) Orbis database to analyze productivity and firm dynamism trends from 2003 to 2018. Orbis has been commonly used to study firm-level productivity issues including misallocation ([Gopinath et al., 2017](#)) and market power ([Díez, Fan and Villegas-Sanchez, 2021](#)), but we are not aware of any other papers which have used Orbis to study firm dynamics in China.<sup>5</sup>

The main benefit of using Orbis is the time horizon it covers. While the commonly used Chinese Industrial Survey (CIS) ends in 2013, Orbis has a broad coverage of manufacturing firms across the size distribution from 2003 to 2018, and gradually increasing

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<sup>5</sup>We use the Orbis "Historical Product" which links several vintages/disks of the Orbis data through firm identifiers to obtain a firm-level longitudinal data set, as described in [Kalemli-Özcan et al. \(forthcoming\)](#).

coverage of service sector firms from 2014 to 2018.<sup>6</sup> Notably, we find that the coverage of firms from 2003 to 2012 is very similar to that in the CIS; from 2003 to 2010 the data only includes firms with annual revenues greater than RMB 5 million, and in 2011-2012 the data only includes firms with annual revenues greater than RMB 20 million. From 2003 to 2012, total revenues aggregated from Orbis average 83% of official aggregates for above-scale manufacturing. From 2013 to 2018, Orbis' coverage of smaller firms expands to include firms with less than RMB 5 million revenues. However, we set a minimum revenue threshold of RMB 5 million in all years to ensure the sample is comparable over time.<sup>7</sup> From 2013 to 2018, total revenues aggregated from Orbis average 70% of official aggregates for above-scale manufacturing, somewhat lower than in the prior decade. Overall, we are reassured by the fact that aggregate manufacturing revenues from our data are 78 percent of official aggregates on average (see Appendix A for more details on the data and sampling).

We measure revenues as sales plus other operating revenues. We measure capital as either total assets or tangible fixed assets. We measure costs as costs of goods sold plus other operating costs. We construct firm age based on the reported year of incorporation. We clean the data in standard ways, dropping firms with missing or zero assets, revenues or costs. We also drop firms where revenues, assets or costs increase or decrease by a factor of 20 or more from year to year. Finally, we trim the 0.5% tails of revenues/costs, revenues/assets and assets/costs. The cleaned manufacturing database contains on average 221,180 firms per year for which we can observe revenues, capital and costs. The final number of observations in each year is reported in Table 3, along with average revenues, costs and capital.

We also classify firms by ownership type. We identify SOEs in our database by combining information from Orbis' own ownership database and also by linking firm identifiers to Wind's ownership database for listed firms (see Appendix B for further details). We identify around 3,200 SOEs every year on average in manufacturing and mining sectors, and 9,200 SOEs every year on average in services sectors for the subperiod 2013-2018.

While Orbis has uniquely broad coverage of manufacturing firms from 2003 to 2018, there are well known issues with Chinese firm-level data. In particular, [Chen et al. \(2019\)](#) and [Brandt et al. \(2023\)](#) estimate substantial over-reporting of value-added and investment in the CIS from 2007 on, worsening over time and large enough to impact macroeconomic aggregates. In contrast to the CIS and China's State Taxation Administration (STA) firm-level survey, data in Orbis is purchased from Chinese credit registries.

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<sup>6</sup>BvD purchases the data in the Orbis database from Chinese credit registries.

<sup>7</sup>All our results are robust to setting the threshold to RMB 20 million.

While credit registries have financial incentives to ensure data validity, a downside of this dataset is that the sample is not designed to be representative at every point in time. Our results are therefore subject to the caveats on the quality of the available data. However, we are reassured about the validity of our findings given they are consistent with other research documenting declining dynamism in the post-GFC period using other datasets, in particular [Brandt et al. \(2023\)](#) who use a methodology combining samples from both the STA and CIS between 2008 and 2013 to correct for measurement error, and [Brandt and Lim \(2020\)](#) who use export-data which is likely to be more accurately measured given customs requirements.

## 2.1. Constructing Manufacturing TFP using Orbis

We check the reliability of our data for understanding trends in China's aggregate TFP by comparing the trend in aggregated firm-level productivity in Orbis to aggregate TFP from the Penn World Tables, as shown in [Figure 1](#). We construct an aggregate TFP series from our firm-level data as a gross-output weighted average of industry-level TFP, based on a Cobb-Douglas industry production function in which gross output is produced from labor, capital and intermediate inputs. We use revenues as our measure of output, tangible fixed assets as our measure of capital, and use industry cost shares to identify labor and intermediate inputs from the sum of cost of goods sold plus non-operating costs. We deflate all variables using 2-digit industry deflators for revenues and intermediate inputs. We construct our sectoral TFP estimates at the same-level as our industry-specific deflators, thereby avoiding the possibility of conflating true productivity growth with changes in markups. See [Appendix C](#) for full details.<sup>8</sup>

Our measure of manufacturing TFP also points to a slowdown in productivity growth post-GFC. In the next section, we document five facts about firm dynamism from 2003 to 2018 which help inform some of the proximate causes of this aggregate productivity slowdown.

## 3. Five Facts about Firm Dynamism in China

We document five facts from the data that show a decline in China's business dynamism. We show that (i) the revenue and capital shares of young firms have declined, (ii) life cycle growth of firms has slowed, (iii) life cycle growth of process efficiency / product

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<sup>8</sup>We acknowledge that our TFP series is not directly comparable in levels to that from the PWT, both because we focus only on manufacturing, and because our production function is in terms of gross output rather than value-added. Our main takeaway instead is the slowdown in both series which occurred around the same period.



quality and investment in intangibles has declined (iv) younger firms have higher capital productivity than older firms, with the gap increasing over time, and (v) the dispersion of capital growth and the responsiveness of capital growth to capital productivity have both declined, particularly for young firms.

**Fact 1: The revenue and asset share of young firms has declined.**

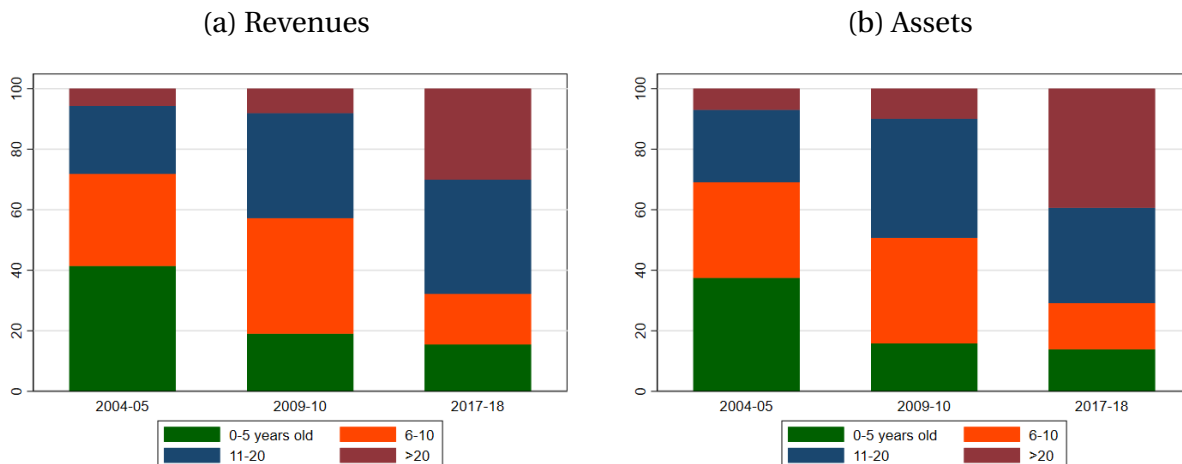
Young firms can be an important driver of aggregate productivity growth (see e.g. Alon, Berger, Dent and Pugsley, 2018). A key moment to quantify their contribution is young firms' share of outputs and inputs (Garcia-Macia et al., 2019). Figure 2 shows the share of revenues and assets accounted for by firms in each age group (0-5, 6-10, 11-20, 21+) in three periods spanning the time horizon we consider: 2004-5, 2009-10 and 2017-18. The revenue share of young firms in China has declined dramatically over time: the share for firms under 10 years old fell from around 70 percent in 2003-04 to around 30 percent in 2017-18. The pattern is very similar when we use total assets as a measure of firm size rather than revenues (Figure 2b).<sup>9</sup> We confirm the external validity of our results outside above-scale manufacturing by measuring the share of revenues and assets accounted for by all firms in the 2013-14 and 2017-18 waves of Orbis, in which there is no revenue threshold. Accordingly, the sample size increases, from 200,000 firms to over 700,000 firms in 2017-18. Figure 14 documents a declining asset and revenue share for young firms from 2013-14 to 2017-18 in this larger sample. In addition, Figure 14b shows that, for the 2017-18 wave, the shares of assets and revenues accounted for by firms in different age groups are very similar to those in our baseline sample (with the minimum size threshold).<sup>10</sup>

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<sup>9</sup>Figure 13 shows that this pattern is also robust to the use of employment as the measure of firm size. We do not use employment as our baseline measure of firm size however because it is less commonly and less consistently reported over time than assets and revenues.

<sup>10</sup>The largest differences are for the relative revenue and asset shares of firms in the 11-20 and 21+ age groups. Firms in the 21+ age group account for 40% assets and 30% of revenues in our baseline sample, but 30% of assets and 40% of revenues in sample including all firms. There is therefore no clear bias due to the minimum threshold. In unreported results, we also find that the share of revenues and assets by age group is similar in services to those in manufacturing.

Figure 2: Revenue and asset share of firms by age group



**Notes:** The figures plot the share of revenues (left) and assets (right) accounted for by firms in four different age-groups: 0-5, 6-10, 11-20 and 21+. The shares are averages across two years during three different periods: 2004-5, 2009-10 and 2017-18. The sample is manufacturing firms with over RMB 5 million in revenues in Orbis.

## Fact 2: Life-cycle growth has declined.

Recent evidence suggests that growth over a typical firm's life cycle tends to be much higher in the U.S. than in developing economies (Hsieh and Klenow, 2014; Haltiwanger, Jarmin and Miranda, 2013; Eslava et al., 2022).

We use Orbis' panel dimension to measure how the life cycles of Chinese firms have changed over time.<sup>11</sup> We estimate average firm growth rates by age group, similarly to Eslava et al. (2022), using the following regression:

$$\Delta_k y_{ist} = \alpha + \sum_{a=1}^5 \beta_a I(\text{age group} = a) + FE_{st} + \epsilon_{ist} \quad (1)$$

where  $\Delta_k y_{ist}$  is the  $k$ -year growth rate (log-change between year  $t$  and  $t + k$ ) for firm  $i$  in sector  $s$  in year  $t$ .  $I(\text{age group} = a)$  are dummies for five different age groups; 1-2, 3-5, 6-10, 11-15 and 16+ (the omitted group).  $FE_{st}$  is a full set of sector year fixed effects. We set  $k = 3$  in order to focus on the medium-run growth dynamics as they move between our broad age categories. Finally, because we are interested in how life cycle growth dynamics have changed over time, we interact the age group dummies with dummies

<sup>11</sup>In the absence of panel data, firms' life cycle growth can be estimated from how the size of firms from the same cohort varies over time, as in (Hsieh and Klenow, 2014).

for the two time periods of interest: 2003-2010 and 2011-2018.<sup>12</sup>

Figure 3a shows the results. Similarly to what has been documented in other countries, we find that average firm growth (conditional on survival) monotonically decreases with age; 3-5 year old firms have growth rates around 17 percentage points higher than firms in the 16+ age group. However, more strikingly, we find that the revenue growth of firms under the age of 10 (relative to 16+) fell by half from 2003-2010 to 2011-2018. The (weighted) average revenue growth of firms under 10 years relative to firms above 16 years of age decreased from 15.3 percent in 2003-2010 to 8.4 percent in 2011-2018. While this pattern is inverted for the youngest firms between 1 and 2 years (startups), there are very few firms in this age group in our dataset (given the revenue threshold for being included in the sample) and the coefficients are not significantly different from each other. We also do not see any difference in the average growth rates of firms 11-15 years of age relative to those 16+ in either period. We also find that life cycle growth of inputs (assets and costs) exhibits a very similar decline to the life growth of revenues.

One possible explanation for the changing life cycle growth of firms is that the average size of entrants changed over time. Growth rates tend to decline with firm size, and so an increase in the average size of entrants could lead to differences in the *measured* life cycle growth of firms even if the economic environment is otherwise unchanged. We address this by additional controlling for initial log(revenues) in Equation 1. Figure 3b shows that our results become *more* pronounced when we control for initial firm size, with even the growth rate of startups being lower in 2011-2018 than in 2003-2010.

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<sup>12</sup>As previously noted, the minimum size of firms in our sample increases to RMB 20 million in 2011 and 2012. This can introduce a selection bias when we consider revenue growth for firms who cross the 20 million threshold (from below or above) in these years. We resolve this by using only observations in 2011 and 2012 where revenues in both  $t$  and  $t + k$  were greater than RMB 20 million. Our results are very similar if we drop 2011 and 2012.

Figure 3: Life cycle revenue growth



**Notes:** These figures plots the 3-year growth rate of revenues without for firms of different age groups, relative to firms in the 16+ age group, controlling for size (left) and controlling for size (right). Bars are plotted separately for 2003-2010 and for 2011-2018. The coefficients are obtained from a regression of 3-year growth rates against sector-year fixed effects and age group dummies. The sample is manufacturing firms with over RMB 5 million in revenues. The left sub-figure shows the coefficients from Equation 1. The right sub-figure includes  $\log(\text{revenues})$  as an additional control.

### Fact 3: Productivity growth and innovation over the life-cycle have weakened.

We consider two main explanations for the decline in life-cycle growth depicted in Figure 3; (a) an increase in frictions impeding firm growth, and (b) a decline in investments by young firms into R&D, process efficiency, quality improvements, or other intangible inputs. Under the assumption of constant returns to scale and constant elasticity of demand, increasing distortions would show up as higher average revenue products (TFPR), while lower efficiency or quality would be captured in TFPQ (Hsieh and Klenow, 2009).<sup>13</sup> We follow [Bils, Klenow and Ruane \(2021\)](#) and measure TFPR as  $Q_{si}/I_{si}$  and TFPQ as  $Q_{si}^{\frac{\sigma}{\sigma-1}}/I_{si}$  where  $Q_{si}$  is firm revenues and  $I_{si}$  is a Cobb-Douglas aggregate of firm inputs.<sup>14</sup> We set  $\sigma = 4$ .

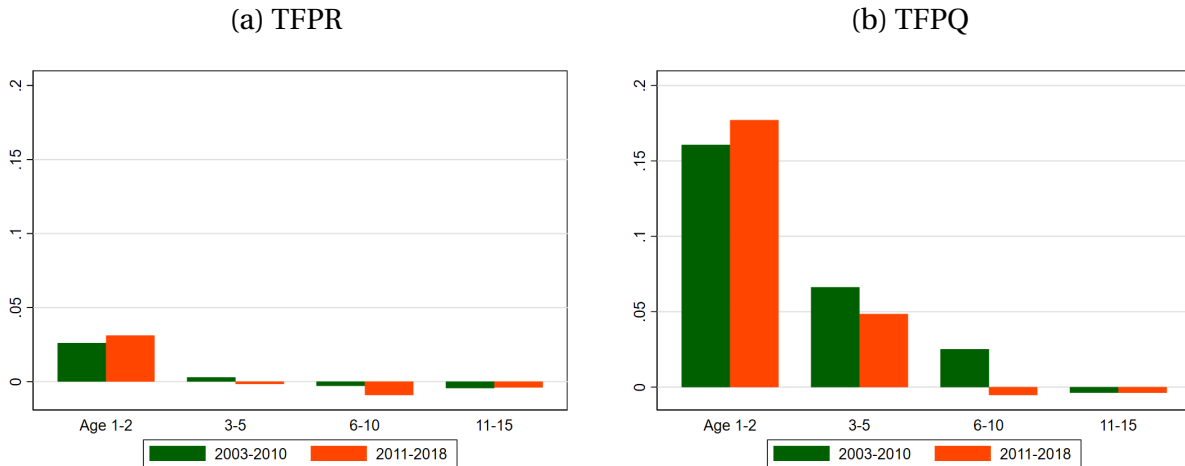
We follow Equation 1 in estimating life cycle dynamics of TFPR and TFPQ and report the results in Figure 4. The left panel shows that TFPR varies little over the life-cycle, apart for very young firms who do see higher average TFPR growth than older firms. This is consistent with evidence that young firms charging initially lower markups in order to build market share ([Foster et al., 2008](#)). While the comparison across periods

<sup>13</sup>This widely adopted TFPR vs. TFPQ notation goes back to [Foster et al. \(2008\)](#).

<sup>14</sup> $I_{si} = (K_{si}^{\alpha_s} w L_{si}^{1-\alpha_s})^{\gamma_s} X_{si}^{1-\gamma_s}$  where  $\alpha_s$  and  $\gamma_s$  are industry cost shares

does suggest a slight weakening of the life cycle of TFPR, the magnitudes are economically small. On the other hand, Figure 4b shows that the life cycle of TFPQ declined substantially over time (apart from very young firms), mirroring the decline in the life cycle of revenue growth.

Figure 4: Life Cycle Growth of TFPR and TFPQ



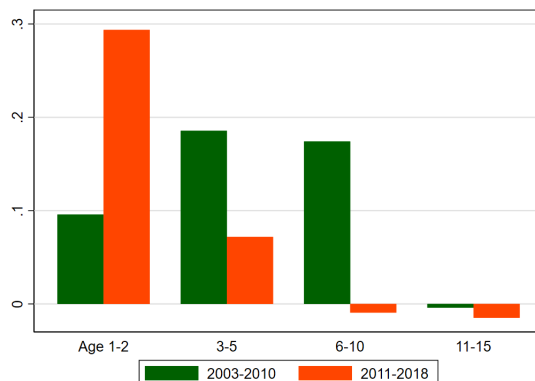
**Notes:** These figures plots the 3-year growth rate of TFPR (left) and TFPQ (right) for firms of different age groups, relative to firms in the 15+ age group. Bars are plotted separately for 2003-2010 and for 2011-2018. The coefficients are obtained from a regression of 3-year growth rates against sector-year fixed effects and age group dummies. The sample is manufacturing firms with over RMB 5 million in revenues.

These results show that weakening growth of process efficiency, product quality or the size of the customer base with age drive the decline in the life cycle, rather than changes in the dynamics of markups or frictions (e.g. financial constraints). While data on innovation efforts are limited, our data contains information on the stock of intangible fixed assets for a subset of the manufacturing firms. We dig further into the sources of the decline in life cycle TFPQ growth by looking at the behavior of intangible investments over the life cycle. Figure 5 shows that young firms (but not startups) during the 2010s indeed invested relatively less in intangibles than they had in the previous decade.<sup>15</sup> The slowing life cycle growth of Chinese firms may therefore be partly explained by a decrease in innovation activities by firms, feeding into a weaker life cycle of productivity.

**Fact 4: The capital productivity gap between young and old firms has increased.**

<sup>15</sup>While there is a increase in the intangible investment rate for startups (firms 1-2 years old), these results are noisy as the sample is limited to around 2500 firms with non-missing intangible asset growth.

Figure 5: Life Cycle Growth of Intangible Assets

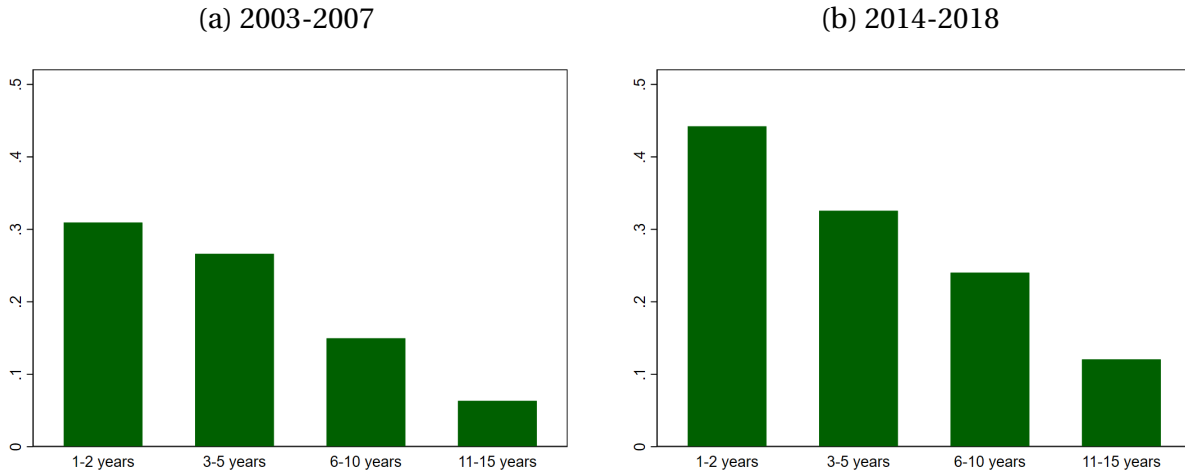


**Notes:** This figure plots the 3-year growth rate of intangible fixed assets for firms of different age groups, relative to firms in the 15+ age group. Bars are plotted separately for 2003-2010 and for 2011-2018. The coefficients are obtained from a regression of 3-year growth rates against sector-year fixed effects and age group dummies. The sample is manufacturing firms with over RMB 5 million in revenues.

Differences in the marginal costs of capital across firms due to financial frictions can lead to capital misallocation, lowering aggregate productivity. While marginal products of capital are unobserved, we follow the standard approach in the literature and measure differences in capital productivity (revenues / capital) between young and old firms to explore the extent to which young firms are capital constrained relative to old firms, and the extent to which these frictions have changed over time.

Figure 6 shows the capital productivity gap of firms in the age groups 1-2, 3-5, 6-10 and 11-15 relative to firms 16 years or older. The left panel shows this relationship for the earliest few years in our sample, 2003-2007. Capital productivity monotonically decreases with firm age, consistent with financial constraints gradually declining as firms get older. The right panel shows the same relationship for the latest years in our sample, 2014-2018. There remains a negative relationship between age and capital productivity, however with a much steeper slope. The gap in capital productivity between firms under 10 years of age and older than 16 increased from 22 percent to 30 percent from the beginning to the end of our sample. This is suggestive of a worsening allocation of capital between young and old firms over time.

Figure 6: Capital Productivity by Age Group



**Notes:** The figure shows a bar chart of the log(revenues / total assets) for firms in different age groups, relative to firms that are in the 16+ age group. The coefficients are obtained from a regression of log(capital productivity) against age group dummies, controlling for sector-year fixed effects. The sample is manufacturing firms in 2003-2007 (left) and 2014-2018 (right) with over RMB 5 million in revenues.

### Fact 5: The responsiveness of capital to capital productivity has declined.

One of the determinants of the allocation efficiency of capital is the extent to which over time capital reallocates towards firms with higher capital productivity. This can be impeded by frictions such as adjustment costs which slow down the rate at which inputs move towards firms whose productivity is growing and away from those whose productivity is shrinking (Asker, Collard-Wexler and De Loecker, 2014).

An important measure of reallocation is the dispersion of input growth, which captures both the dispersion in the shocks that firms are hit by and the extent to which these shocks result in inputs moving. Dispersion in input growth tends to be higher when the economy has many high-growth firms (Akcigit and Ates., 2019a,b), and so is an important metric for understanding market dynamism. We find that dispersion in total asset growth has declined by one third over time, from 0.126 in 2003-2007 to 0.083 in 2014-2018.<sup>16</sup>

We use the panel dimension of Orbis to directly evaluate whether capital is moving towards the firms with the highest capital productivity with the following specification:

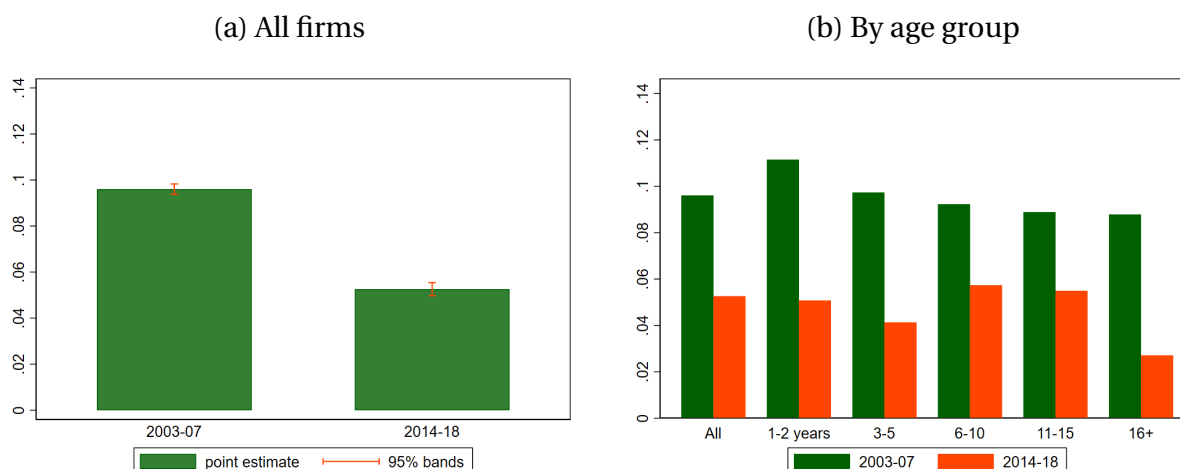
$$\Delta k_{ist} = \alpha + \beta k_{ist} + \gamma arp_{k_{ist}} + FE_{st} + \nu_{ist} \quad (2)$$

<sup>16</sup>We focus on total assets as our measure of inputs because it is reported by all firms in our database.

where  $\Delta k_{ist}$  is the growth rate of capital of firm  $i$  in sector  $s$  between year  $t$  and  $t + 1$ .  $k_{ist}$  is  $\log(\text{capital})$  in year  $t$  and  $arpk_{ist}$  is  $\log(\text{capital productivity})$  in year  $t$ .  $FE_{st}$  is a full set of sector-year fixed effects. We estimate the coefficient  $\gamma$  separately across time periods and firm age groups (estimated by including an interaction term in Equation 2). A higher value of  $\gamma$  indicates that capital is growing more for firms with high capital productivity, suggesting a more efficient reallocation of capital.

We report the estimated coefficients in Figure 7. Figure 7a shows that the responsiveness of capital growth to capital productivity declined from 0.096 in 2004-2007 to 0.059 in 2016-2018. Figure 7b) reports the coefficients estimated separately by age group. The decline in capital responsiveness is particularly pronounced for very young firms (under 5 years of age) whose capital productivity is very high (Figure 6). Notably, the decline in responsiveness is also large for old firms (16+) whose capital productivity is very low, and who therefore would be expected to see their capital stock relatively shrink. The overall decline in capital responsiveness is therefore particularly driven by limited capital reallocation from older to younger firms.

Figure 7: Response of capital growth to (log) average capital productivity



**Notes:** The left figure shows the coefficients (and 95% confidence intervals) obtained from firm-level regressions of capital growth against the lagged  $\log(\text{average product of capital})$  and lagged  $\log(\text{total assets})$ , controlling for sector-year fixed effects. We run the regression separately for the first three years and last three years of our sample. The right figure plots the coefficients from the same regression by age group. The sample is manufacturing firms with over RMB 5 million in revenues.



## 4. The Aggregate Impact of Declining Dynamism

In this section we use a simple model to quantify the potential aggregate impacts of the decline in life-cycle dynamism and worsening capital allocation documented in the previous section.

Aggregate output is a CES aggregate of the output produced by individual firms:

$$Y = \left( \sum_i Y_i^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \quad (3)$$

Firms are monopolistic competitors and produce output using capital:  $Y_i = A_i K_i$ . They maximize profits subject to an idiosyncratic capital distortion, and take the rental rate and downward sloping demand curve as given:

$$\max \quad P_i Y_i - (1 + \tau_i^K) R K_i \quad (4)$$

We can derive from the first order condition that revenue productivity in this model (TFPR) depends on the common rental rate  $R$ , the common markup  $\left( \frac{\sigma}{\sigma-1} \right)$  and the firm's idiosyncratic distortion, but does not depend on firm process efficiency  $A_i$ :

$$\text{TFPR} \equiv \frac{P_i Y_i}{K_i} \propto (1 + \tau_i^K) \quad (5)$$

TFPQ in turn is proportional to  $A_i$ , consistent with the analysis in Section 3.

$$\text{TFPQ} \equiv \frac{(P_i Y_i)^{\frac{\sigma}{\sigma-1}}}{K_i} \propto A_i \quad (6)$$

The capital stock is fixed and normalized to one, and we can therefore derive that aggregate output, which is also equal to aggregate productivity, is given by the following expression:

$$Y = \left( \sum_i A_i^{\sigma-1} \left( \frac{1 + \tau_i^K}{1 + \tau^K} \right)^{1-\sigma} \right)^{\frac{1}{\sigma-1}} \quad (7)$$

Grouping firms by age group  $a$ , we can express aggregate productivity as the product of an 'old' incumbent productivity term, a life-cycle term, and an allocative efficiency

term:

$$Y = A^{\text{old}} \cdot \underbrace{\left( \sum_a \sum_i^{N_a} \left( \frac{A_{a,i}}{A^{\text{old}}} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}}}_{A^{\text{lc}}=\text{Life-Cycle Productivity}} \cdot \underbrace{\left( \sum_a \sum_i^{N_a} \left( \frac{A_{a,i}}{\bar{A}} \right)^{\sigma-1} \left( \frac{1 + \tau_{a,i}^K}{1 + \bar{\tau}^K} \right)^{1-\sigma} \right)^{\frac{1}{\sigma-1}}}_{AE=\text{Allocative Efficiency}} \quad (8)$$

Aggregate productivity *growth* can then be decomposed as follows:

$$\Delta \log(Y) = \Delta \log(A^{\text{old}}) + \Delta \log(A^{\text{lc}}) + \Delta \log(AE) \quad (9)$$

We use this model decomposition to quantify how the decline in life-cycle dynamism and worsening capital allocation between young and old firms has contributed to declining productivity growth in China.

Abstracting from entry and exit and for small changes in productivity,  $\Delta \ln(A^{\text{lc}})$  can be approximated as the capital share weighted average of productivity growth:<sup>17</sup>

$$\Delta \ln(A^{\text{lc}}) = \sum_a \sum_i^{N_a} \left( \frac{\overline{K_{a,i}}}{\bar{K}} \right) \Delta \ln \left( \frac{A_{a,i}}{A^{\text{old}}} \right) = \sum_a \left( \frac{\overline{K_a}}{\bar{K}} \right) \Delta \ln \left( \frac{\bar{A}_a}{A^{\text{old}}} \right) \quad (10)$$

where  $\left( \frac{\overline{K_a}}{\bar{K}} \right)$  is the average capital share of firms in age group  $a$  and  $\Delta \ln \left( \frac{\bar{A}_a}{A^{\text{old}}} \right)$  is the relative TFPQ growth of firms in age group  $a$  relative to old firms. We construct the weights for different age groups  $\left( \frac{\overline{K_a}}{\bar{K}} \right)$  using the asset shares from Figure 2b, and the growth rates of TFPQ of firms in different age groups relative to old firms from Figure 4b.<sup>18</sup> We find that the decline in life-cycle dynamism between 2003-2010 and 2011-2018 contributed to a 2.3 p.p. decline in manufacturing productivity growth every 3-years, or roughly 0.8 p.p. annually. 53% of this decline comes from the lower asset share of younger firms with higher growth rates (changes in the weights), with the remaining 47% stemming from the relative decline in the productivity growth rates of younger firms.

Secondly, we use the model to estimate the change in allocative efficiency resulting from the changes in capital productivity across firm age groups (Figure 6). Baqaee and Farhi (2022) show that, up to a second order, the losses from misallocation can be

<sup>17</sup>As shown in Hsieh and Klenow (2018), the correct weights in this expression are Sato-Vartia input shares, however for small changes in inputs these are approximately equal to Tornqvist input shares.

<sup>18</sup>We average the 2003-04 and 2009-10 capital shares for the early period weights, and the 2009-10 and 2017-18 capital shares for the later period weights.

expressed as the sales-weighted variance of distortions:

$$\ln(AE) \approx \frac{\sigma}{2} \text{var}^\lambda(\log(\text{TFPR}_i)) \quad (11)$$

Given our focus on productivity and distortions across age groups, we abstract from dispersion in distortions within-age groups, and calculate the change in the revenue-weighted variance between 2003-2007 and 2014-2018. We set  $\sigma = 4$  and calculate allocative efficiency in each period as:<sup>19</sup>

$$\ln(AE) = \frac{\sigma}{2} \sum_a \left( \frac{R_a}{R} \right) (\log(\text{ARPK}_a) - \overline{\log(\text{ARPK})})^2 \quad (12)$$

We find that manufacturing productivity is 1.25 percent lower in the later period due to worsening capital allocation across age groups. This corresponds to a roughly 0.12 p.p. annual decline in TFP due to worsening capital allocation across firm age groups.

Our exercises in this section are admittedly simple, relying on strong assumptions and abstracting from relevant margins such as entry and exit. However, they provide a rough idea of the potential impact of the decline in dynamism described in the previous section on aggregate productivity in China. We leave it to future research to use richer models to explore the magnitudes of additional margins and the specific impacts of policy frictions.

## 5. Explaining China's Declining Business Dynamism

Why did China's business dynamism slow down so dramatically during the 2010s? Many factors are most likely at play given that similar trends have been observed in other countries. For example, both changing demographics and rising market power have played a role in driving the decline of U.S. business dynamism (Pugsley and Şahin, 2018; Akcigit and Ates., 2019b). It is outside the scope of this paper to evaluate the importance of all factors potentially contributing to this trend in China. Instead, we investigate one factor that is particularly relevant for China – the role played by state-owned enterprises. There are two main reasons to consider SOE intensity as a factor in explaining the decline in China's business dynamism. Firstly, Brandt et al. (2020a) find that regional state presence is an important factor in reducing the creation of new firms prior to 2008, suggesting that SOE presence may indeed reduce business dynamism. Secondly, China's growth spurt in the 2000s happened during a period of large-scale SOE reform (the SOE

<sup>19</sup>As before we average the 2003-04 and 2009-10 revenue shares for the early period weights, and the 2009-10 and 2017-18 revenue shares for the later period weights.

share of industrial assets declined from over 54 percent in 2003 to below 43 percent in 2008), while the productivity slowdown has coincided with a plateauing of the share of SOE among industrial firms, with SOEs still accounting for 39 percent of assets in 2019 despite substantially lower capital productivity. In this section, we first show that large revenue and capital productivity gaps between SOEs and private firms have persisted throughout the 2010s. We then estimate the correlation between SOE intensity and our two main measures of business dynamism: the life-cycle growth of young firms and the responsiveness of capital growth to capital productivity.

### 5.1. SOE-Private Firm Productivity Gaps

Many papers have documented large revenue productivity gaps between SOEs and private firms using data on above-scale industrial firms through 2013 (Hsieh and Klenow, 2009; Berkowitz, Ma and Nishioka, 2017; Bai et al., 2018), which are often interpreted as reflecting significant resource misallocation. These productivity gaps have also been found for the more recent period (through 2019) among listed firms and shown to be a quantitatively important of resource misallocation (Jurzyk and Ruane, 2021). However, there is limited evidence about whether the earlier findings for manufacturing firms hold true for non-listed firms post-2013, or whether these productivity gaps exist outside of manufacturing.

Our data allow us to measure these gaps from 2003 to 2018 for a large sample of non-listed firms manufacturing sectors, as well as service sectors from 2013 to 2018. We run the following regressions to estimate the SOE productivity gaps:

$$arp_{ist} = \alpha + \beta SOE_{ist} + FE_{st} + \nu_{ist} \quad (13)$$

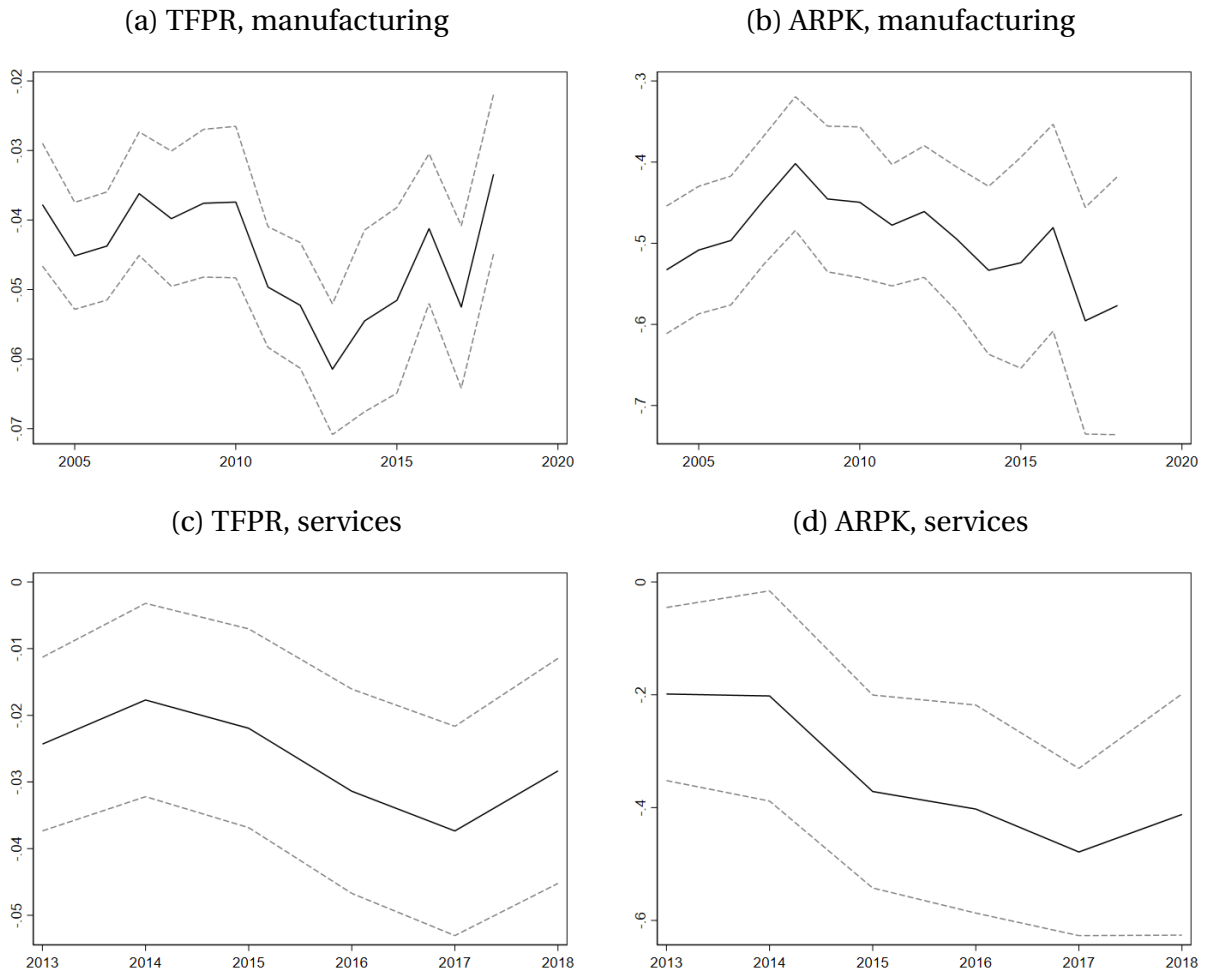
where  $arp_{ist}$  is either firm-level TFPR or capital productivity, and  $SOE_{ist}$  is a dummy variable identifying SOEs (see Appendix B for details on how we identify SOEs in Orbis). We control for sector-year fixed effects  $FE_{st}$  to ensure that the measured gaps do not reflect the fact that SOEs tend to be present in more established or more capital-intensive sectors. Figure 8a shows that SOEs have consistently had lower revenue productivity than private firms, with an average revenue productivity gap of around 4-5 percent.<sup>20</sup> As found in most of the earlier literature, these gaps are almost exclusively explained by SOEs' lower capital productivity, as shown in Figure 8b. The gaps for services, es-

<sup>20</sup>Differences in the magnitude of the measured gaps vis-a-vis Jurzyk and Ruane (2021) are due to the fact that we measure productivity as the ratio of revenues to inputs, while they used value-added to inputs.

estimated for the 2013-2018 period in which services-sector coverage increases in Orbis, are somewhat smaller but still statistically and economically significant.

These findings confirm that the low revenue productivity of SOEs has remained a feature of the Chinese economy throughout the 2010s. [Hsieh and Klenow \(2009\)](#) and many others have studied the implications for misallocation - reallocating resources from SOEs to private firms could increase aggregate productivity. However, in what follows we explore a second channel through which SOE reform could potentially increase aggregate productivity, by increasing life cycle dynamism of private firms.

Figure 8: SOE productivity gaps



**Notes:** The figures plot the coefficients from regressions of  $\log(\text{TFPR})$  and  $\log(\text{ARPK})$  against SOE dummies and sector-year fixed effects. TFPR is revenue productivity, measured as firm revenues divided by the geometric average of assets and costs, with weights given by industry cost shares. ARPK is capital productivity, defined as revenues divided by total assets. We plot the coefficients on the SOE dummies separately for firms in manufacturing and firms in services, for which we have a smaller sample. See Appendix B for more details on how the SOE dummies are constructed.

## 5.2. Life-Cycle Growth and SOE Intensity

We use our data on manufacturing firms to explore how life cycle growth varies with provincial SOE intensity. We construct provincial SOE intensity as the share of total assets in the province accounted for by SOEs.<sup>21</sup> We measure life cycle growth as previously

<sup>21</sup>We use assets because data on employment and other inputs is more limited in Orbis, while assets are reported for all firms.

described - we construct the 3-year average growth rates of young firms (age < 5) relative to old firms (16+) in each province-year, and regress these against initial SOE intensity. We run the following regression at the province-year level:

$$lc_{pt} = \alpha + \beta SOEI_{pt} + FE_p + FE_t + \nu_{pt} \quad (14)$$

where  $lc_{pt}$  is our measure of life-cycle growth (revenues, assets, TFPQ and intangibles),  $SOEI_{pt}$  is SOE intensity, and  $FE_p$  and  $FE_t$  are province and year fixed effects respectively. The year fixed effects control for common time trends in life cycle growth and SOE intensity, which is important given that we have previously documented that at the aggregate level life cycle growth has fallen while SOE intensity has plateaued. The province fixed effects control for any time-invariant province characteristics. The coefficient  $\beta$  is therefore identified by *relative* changes in province-level SOE intensity and life cycle growth.

We report our results in Table 1. We find that young firms operating in provinces with higher SOE intensity tend to have weaker revenue growth, capital growth, and TFPQ growth (columns 1-3). The coefficients for revenue and capital growth are economically and statistically significant, while the the coefficient for TFPQ growth is not statistically different from zero. The last column in Table 1 also reports the association between intangible asset growth and SOE intensity. While it also has a negative sign, the coefficient is very imprecisely estimated. Overall, being in a province with 10 percentage point higher SOE share of assets is associated with 3.5 percent lower 3-year revenue and input growth for young firms, relative to an average 3-year growth rate of 17.5 percent. Table 4 reports broadly similar results run for the period 2013-2018, during which life-cycle dynamism was particularly low. The association between life-cycle revenue growth and TFPQ growth and SOE intensity is statistically significant and more negative than in the full sample, while the coefficient on the life-cycle of asset growth is not statistically different from zero. We also run Equation 14 at the sector-year level rather than at the province-year level. At this level, we do not find any association between life-cycle growth and SOE intensity, however.<sup>22</sup>

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<sup>22</sup>These results available upon request.

Table 1: Province-level young firm life-cycle growth vs. provincial SOE intensity

VARIABLES	(1)	(2)	(3)	(4)
	3-year revenue growth	3-year asset growth	3-year TFPQ growth	3-year intangibles' growth
State presence	-0.00349** (0.00147)	-0.00291** (0.00136)	-0.00120 (0.000867)	-0.00503 (0.0110)
Constant	0.271*** (0.0485)	0.233*** (0.0448)	0.0945*** (0.0286)	0.0540 (0.372)
Observations	362	363	362	210
R-squared	0.268	0.196	0.254	0.233
Age	1-5	1-5	1-5	1-5
Years	All	All	All	All
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES

Notes: Table 1 reports results from province-year level regressions of the relative growth of young vs. old firms (in revenues, assets, TFPQ and intangibles) against province-year level measures of state presence. Young firms are those between the ages of 1 and 5, while older firms are those whose age is 16+. We include province and year fixed effects in all regressions.



### 5.3. Capital Reallocation and SOE Intensity

We also use the richness of our data to explore how the responsiveness of capital to capital productivity among private firms varies with local SOE intensity. We divide provinces into high and low SOE intensity provinces. We extend Equation 2, interacting capital growth with a dummy for high province-level intensity:

$$\Delta k_{ist} = \alpha + \beta k_{ist} + \gamma arp k_{ist} + \lambda arp k_{ist} \times SOEIH_p + FE_{st} + FE_p + \nu_{ist} \quad (15)$$

where  $SOEIH_p$  is a dummy for provinces with high SOE intensity. In addition, we include province fixed effects  $FE_p$  to control for time-invariant province-level characteristics. As before, we estimate separate elasticities for each period: 2003-2007 and 2014-2018. We report our results in Table 2. We do not find a significant link between provincial SOE intensity and capital responsiveness in 2003-2007 (column (1)). However, in the 2014-2018 period, we find that provinces with high SOE intensity have significantly lower capital responsiveness. Being in a state with high SOE intensity is associated with a 3.25 percentage point lower elasticity of capital growth to capital productivity.

### 5.4. Potential Mechanisms

We highlighted three main findings in this section. Firstly, revenue and capital productivity gaps between SOEs and private firms have persisted through the late 2010s. Secondly, life-cycle growth of young firms tends to be lower in provinces with larger SOEs, but there is no correlation between life-cycle growth and sectoral SOE intensity. Thirdly, capital reallocation to high capital productivity firms is lower in provinces with high SOE intensity. While our findings do not prove a causal link of negative local spillovers from SOEs to private firm dynamism, existing research has documented a number of mechanisms which could explain them, which we discuss below.

One explanation is local capacity constraints leading to the crowding out of the private sector. SOEs tend to provide greater job security for workers than private firms, and young firms tend to be inherently riskier due to high exit rates. It may therefore be harder for young firms to hire talented workers in local markets where workers have more outside options in SOEs. Similar capacity constraints and inefficiencies could also be relevant in capital markets. An extensive literature documents the advantages that SOEs have in obtaining capital financing from banks (Bai et al., 2018), in part because they may be perceived as benefiting from implicit government guarantees. The efficiency of the local banking system for capital allocation may therefore be worse in SOE-intensive regions, leading to relatively lower financing availability for young private

Table 2: Province-level capital responsiveness vs. provincial SOE intensity

VARIABLES	(1) 1-year Capital growth	(2) 1-year Capital growth
log(Average Product of Capital)	0.114*** (0.000923)	0.0766*** (0.00161)
High State Presence	-0.000944 (0.00359)	0.00703 (0.00520)
log(ARPK) x High State Presence	0.00171 (0.00188)	-0.0325*** (0.00395)
Constant	0.0709*** (0.000936)	0.0637*** (0.00101)
Observations	601,764	186,697
R-squared	0.060	0.046
Years	2003-2007	2014-2018
Sector-Year FE	YES	YES
Province FE	YES	YES

**Notes:** Table 2 reports results from firm-year level regressions of capital growth against log(ARPK), a dummy for provinces with high state presence and the interaction between log(ARPK) and high state presence. We run the regression separately for the first and last 4 years of our sample.

firms in particular, leading in turn to large capital productivity gaps. Another mechanism is local regulations, which may be introduced given the political economy problems discussed in [Brandt et al. \(2020a\)](#). Local governments and local SOEs tend to be closely linked, with local governments feeling pressure to ensure the viability of SOEs. Out of a concern that young firms could threaten the position of local SOEs through product market competition and competition for local factors of production, local governments in regions with more SOEs may therefore introduce regulatory barriers to make it harder for young firms to grow.

It is also important to note that many policy changes unrelated to SOEs occurred during the period we consider in this paper. This includes changes to how industrial policies and targeted subsidies were implemented ([Naughton, 2022](#)). The financial crisis also led to a considerable increase in local public debt and government infrastructure investments which may have had spillover impacts on private firms. In particular, [Huang, Pagano and Panizza \(2020\)](#) show that this increase in local public debt crowded out investment by private firms and made them more sensitive to internal cash flows. China's role in global trade also expanded dramatically following WTO accession. This led to productivity improvements amongst private manufacturing firms ([Brandt et al., 2017](#)), as well as greater FDI. Labor policies also changed, with differential changes in minimum wages across regions affecting private firm growth ([Hau, Huang and Wang, 2019](#)), and the loosening of 'hukou' migration restrictions enabled greater cross-province migration ([Tombe and Zhu, 2019](#)). We hope that future research will further explore how important these various channels have been in driving trends in the life-cycle dynamism of Chinese firms.

## 6. Conclusion

After impressive growth in the 2000s, China's aggregate productivity has stagnated in the 2010s. We use firm-level data to analyze productivity and firm dynamism trends from 2003 to 2018. We construct a bottom-up estimate of manufacturing productivity from our data and confirm the productivity growth slowdown. We then document five novel facts about China's business dynamism: (i) the revenue and capital shares of young firms have declined, (ii) life cycle growth of firms has slowed, (iii) life cycle growth of process efficiency / product quality and investment in intangibles has declined (iv) younger firms have higher capital productivity than older firms, with the gap increasing over time, (v) the dispersion of capital growth and the responsiveness of capital growth to capital productivity have both declined. We use a simple model to show that these trends may have had quantitatively important effects on aggregate manufacturing pro-

ductivity in China. In the cross-section of provinces, we find that where SOEs account for a larger share of assets, business dynamism tends to be weaker. The findings underscore that stimulating business dynamism may be an additional source of productivity gains from SOE reform.

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## A Data Appendix

The main dataset we use in the paper is from Bureau Van Dijk's Orbis database. The data has extensive coverage of the Chinese manufacturing sector from 2003 to 2018. Similarly to the commonly used Chinese Industrial Survey, from 2003 to 2010, the data is collected for firms with more than 5 million RMB in revenues. In 2011 and 2012, the database only has information for firms with revenues over a 20 million RMB threshold. From 2013 to 2018, there is no minimum revenue threshold. In order to preserve comparability of our sample over time, we restrict our attention to firms with at least 5 million RMB in revenues in all years, and check robustness to setting this threshold to 20 million RMB in all years. From 2003 to 2012, total revenues aggregated from Orbis average 83% of official aggregates for above-scale manufacturing. From 2013 to 2018, the corresponding share declines somewhat to 70% of official aggregates.

The main capital variables we use are tangible fixed assets, fixed assets and total assets. Total assets are reported by all firms in all years, while tangible fixed assets and fixed assets are missing in some years. For the years in which these are missing, we impute them using industry shares and the firm's reported total assets.<sup>23</sup> We construct costs as cost of goods solds + other operating costs. These include both labor costs and material inputs. Because employment and labor costs are not commonly reported in Orbis, we don't separate materials from labor costs. We measure revenues as total operating revenues, which includes sales and other revenues. We clean the data in standard ways, dropping firms with missing or zero assets, revenues or costs. We also drop plants where revenues, assets or costs increase or decrease by a factor of 20 or more from year to year. Finally, we trim the 0.5% tails of revenues/costs, revenues/assets and assets/costs. The final number of observations in each year are reported in Table 3, along with and average revenues, costs and capital.

## B State Ownership Data

We classify firms' ownership between private and state-owned by combining information two sources, WIND and Orbis. For listed firms, we use WIND data that classify firms each year into private or state-owned. For unlisted firms, we resort to Orbis' historical ownership databases. Specifically, we classify as state-owned those firms that in Orbis show up as having a Global Ultimate Owner controlling at least 50 percent of the company that for which the entity type is "S" (i.e. the state).

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<sup>23</sup>We impute tangible fixed assets from fixed assets in 2003, and fixed assets from tangible fixed assets in 2010. We impute both fixed assets and tangible fixed assets from total assets in 2014, 2017 and 2018.

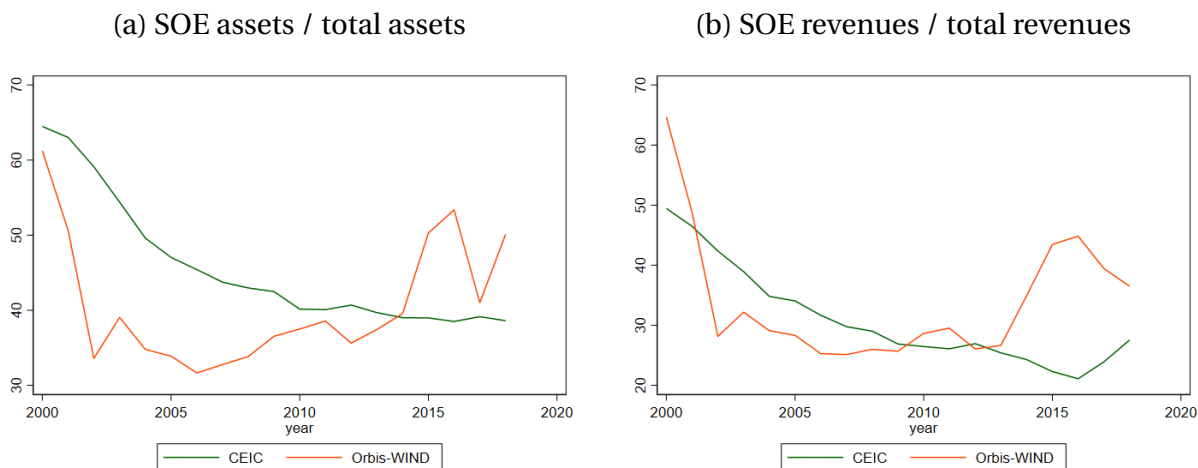


Table 3: Summary statistics for manufacturing firms from Orbis

	Observations	Revenues	Costs	Total Assets	Tangible Fixed Assets
2003	86,968	91,636,403	85,481,774	94,817,986	36,034,866
2004	161,234	73,647,919	69,086,726	69,417,834	26,456,472
2005	180,741	92,110,839	86,920,457	79,579,964	30,092,239
2006	265,105	101,337,358	94,970,617	82,154,171	29,952,293
2007	303,623	116,731,065	107,981,800	92,800,197	32,772,664
2008	353,580	111,435,921	104,431,020	87,078,285	30,141,470
2009	294,682	132,614,342	123,542,275	108,783,969	36,732,682
2010	262,169	153,797,953	142,712,045	125,190,272	40,524,759
2011	242,957	276,088,841	256,496,768	213,095,978	71,524,902
2012	235,888	292,644,457	273,609,596	230,397,440	73,899,523
2013	250,795	29,5314,973	276,183,723	239,986,516	77,116,929
2014	241,776	225,927,394	214,976,571	253,124,775	75,962,412
2015	98,698	425,288,257	412,465,565	545,848,812	161,837,954
2016	125,465	434,359,175	410,411,028	592,013,264	167,105,593
2017	155,087	519,030,692	499,327,685	724,920,665	184,086,506
2018	280,115	329,358,590	321,326,740	548,890,078	137,220,768

Notes: This table reports the number of observations in the cleaned Orbis manufacturing database in each year, along with average revenues, costs, total assets and tangible fixed assets.

**Figure 9:** Aggregate state presence: CEIC vs. Orbis-WIND estimates



For the analysis that correlates business dynamism with state presence at the sector/province level, we use the last-observed POE/SOE classification for the specific firm ID. For those firms where we observe the classification at least twice, 1.16 percent show a transition from POE to SOE, and 0.42 percent show a transition from SOE to POE. Transitions thus appear to be overall relatively rare, suggesting that using ‘last-observed’ SOE status should not lead to large measurement issues.

Figure 9 compares the time series of aggregate SOE assets (Figure 9a) and SOE revenues (Figure 9b) in percent of totals as derived from Orbis-WIND, with the corresponding aggregates published by the National Bureau of Statistics (NBS) and compiled by CEIC.<sup>24</sup> In doing this comparison, we restrict attention to those sectors for which CEIC has data, namely NACE 2-digits going from 5 to 36 (mining, manufacturing, and utilities). Our bottom-up estimates broadly match the official percentages in levels, and show the decline of the early 2000s. Since around the GFC, however, it is worth noting that our bottom-up estimates show a slight upward trend not present in the official data.

In our analyses in the main text, however, we mainly exploit the cross-sectional variation in state presence in Section 5. Figure 10 shows that, in the cross-section, our bottom-up estimates of state presence tend to be highly correlated with those that can be obtained from CEIC data. As a reference, Figure 11 zooms into the 2018 comparison. While in less than a handful of cases our measure disagrees with CEIC data (machinery repair, water supply), by and large it appears to accurately gauge the extent of state presence.

<sup>24</sup>CEIC Data is available from <https://www.ceicdata.com>.

Figure 10: State presence by assets and revenues: cross-sectional (across sectors) correlations between CEIC and bottom-up Orbis-WIND estimates, by year

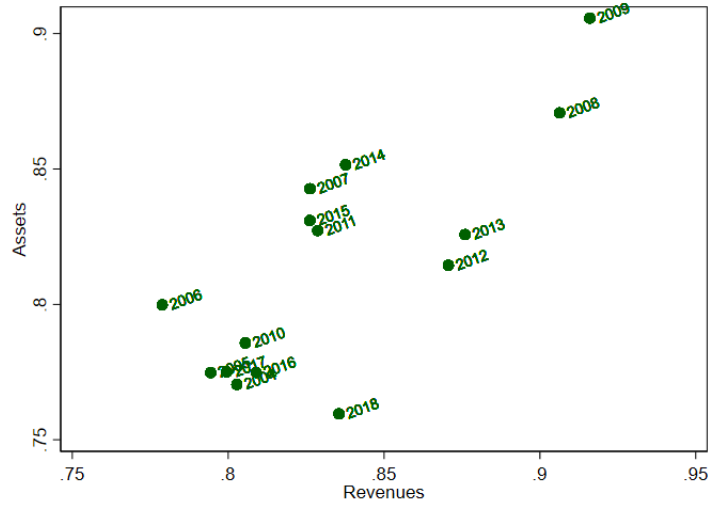
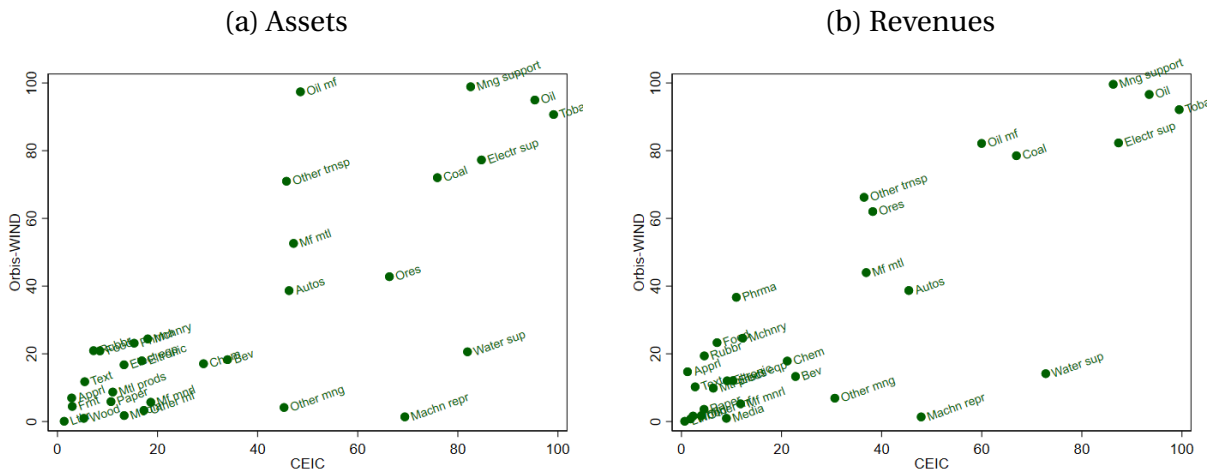


Figure 11: State presence by assets and revenues in 2018 for different sectors



## C Constructing Sectoral TFP Measures

We start by positing a sectoral production function

$$Q_{jt} = A_{jt}(K_{jt}^{\alpha_s} L_{jt}^{1-\alpha_j})^{\gamma_j} X_{jt}^{1-\gamma_j},$$

where  $Q$  denotes gross output,  $K$  is capital,  $L$  is labor inputs,  $X$  is intermediate inputs, and  $A$  is sectoral TFP.  $\alpha_s$  is the capital share (of value-added) and  $\gamma_s$  is the capital and labor share of gross output. As is customary, the idea is to construct sectoral TFP as a residual (no capitalization indicates variables are in logs):

$$a_{jt} = q_{jt} - \gamma_j(\alpha_j k_{jt} + (1 - \alpha_j)l_{jt}) - (1 - \gamma_j)x_{jt}. \quad (16)$$

We define these production functions at the 2-digit (i.e. “Division”) level of the NACE Rev. 2 classification. Next we construct TFP at the sector  $s$  level (e.g. manufacturing) by aggregating our industry TFP measures using each industry’s gross output share:

$$a_{st} = \sum_{j \in s} \frac{P_{jt} Q_{jt}}{P_{st} Q_{st}} a_{sjt}.$$

The remainder of this appendix describes the data used to construct all the variables in equation (16). In constructing the estimates we use extensively WIOD’s global input-output data (Timmer, Dietzenbacher, Los, Stehrer and de Vries, 2015). Orbis uses the NACE Rev. 2 industry classification. WIOD follows the ISIC Rev. 4 classification. We create a concordance between these two classifications.<sup>25</sup>

*Nominal variables.* Nominal gross output is measured as Operating revenue, and capital as Tangible fixed assets. Ideally one would measure the nominal wage bill using Cost of employees, and nominal spending in intermediate inputs using material costs. Given that these are missing for many firms in the sample, we use instead Cost of goods sold plus Operating expenses to measure the sum of the nominal wage bill and nominal spending in intermediates. We impute each component using WIOD’s Socio Economic Accounts data for compensation of employees (COMP) and intermediate-input spending (II), using the average for 2003-2014.

*Gross-output deflators.* For most WIOD sectors a corresponding PPI index is available

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<sup>25</sup>WIOD’s data contain a total of 56 sectors. There are no firms in sectors 55 (Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use) and 56 (Activities of extraterritorial organizations and bodies) in Orbis. These sectors are omitted from the analysis.

from NBS (retrieved from CEIC). This is not the case for some services sectors. As a result, for those services sectors we use the GDP deflator for the closest-matching sector (retrieved from Haver). Given that these are services, and hence less-tradable sectors, sectoral GDP deflators should closely follow the overall producer-price movements for these sectors.

*Intermediate-input deflators.* The intermediate-input deflator of a sector  $s$  is calculated as the weighted average of the gross-output deflators of all sectors, where the weights are given by sector  $s$ 's 2004-2014 purchases from each sector. The sectoral purchase data are from WIOD.

*Capital deflator.* Capital is deflated using the NBS Fixed Asset Investment price index (retrieved from CEIC).

*Wage deflators.* Wage deflators are from NBS.

*Production elasticities.* To construct industry-specific production elasticities  $\alpha_{jt}$  and  $\gamma_{jt}$ , we first assume a rental rate of capital of 0.2 (Bils et al., 2021). Production elasticities are then readily calculated as the capital share of value added and the capital-cum-labor share of gross output, over the entire 2004-2016 sample. That is,

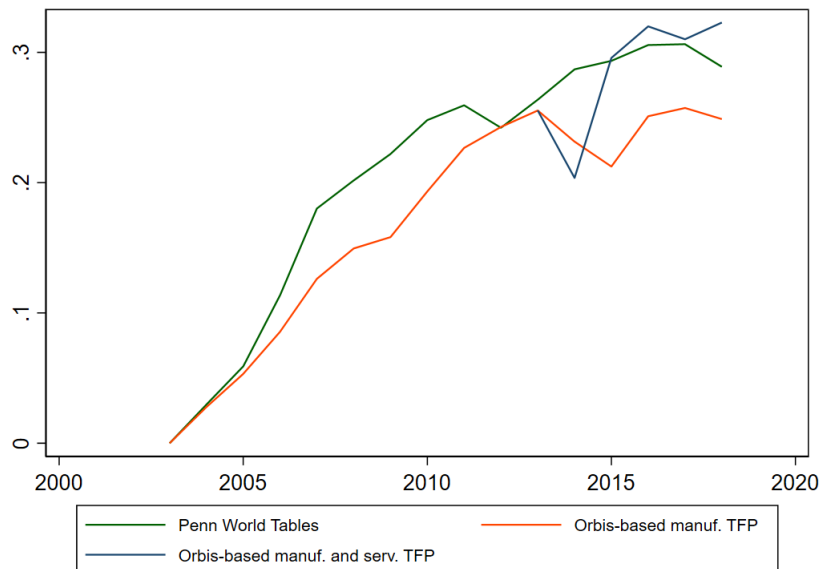
$$\alpha_{jt} = \alpha_j = \frac{R\bar{K}_j}{R\bar{K}_j + \bar{w}\bar{L}_j},$$

$$\gamma_{jt} = \gamma_j = \frac{R\bar{K}_j + \bar{w}\bar{L}_j}{R\bar{K}_j + \bar{w}\bar{L}_j + \bar{P}^x\bar{X}_j},$$

where  $R = 0.2$  and bars over variables denote average values.

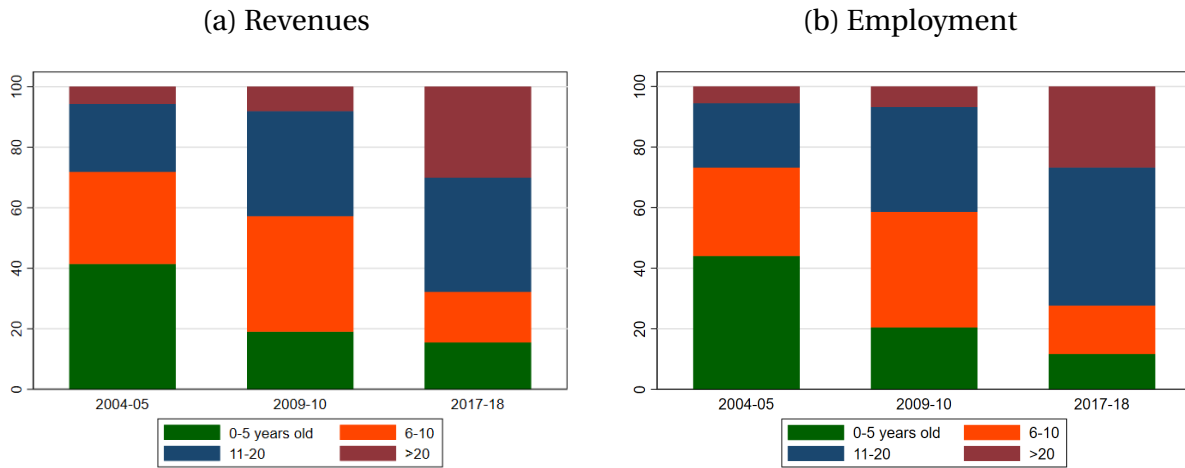
## D Additional Figures

Figure 12: Orbis (Manufacturing and Services) and PWT Productivity (log-scale)



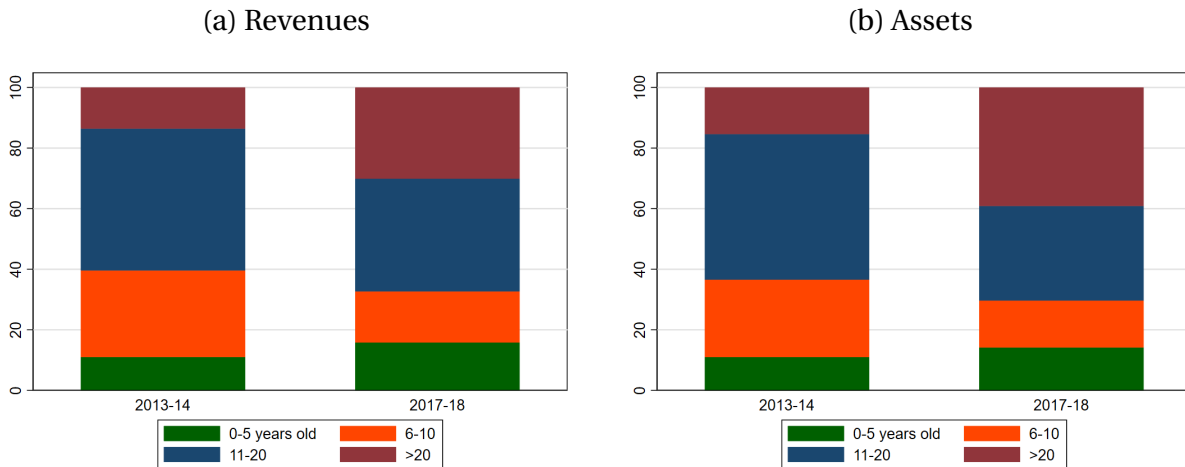
**Notes:** The figure plots TFP on a log-scale (y-axis in log points) and normalized to 0 in 2003. The green line reports aggregate TFP from the Penn World Tables. The orange line reports manufacturing TFP constructed from the Orbis database (methodology described in the text). The blue line incorporates Orbis data for service sector firms from 2014 to 2018.

Figure 13: Revenue and employment share of firms by age group



**Notes:** The figures plot the share of revenues (left) and employment (right) accounted for by firms in four different age-groups: 0-5, 6-10, 11-20 and 21+. The shares are averages across two years during three different periods: 2004-5, 2009-10 and 2017-18. The sample is manufacturing firms with over RMB 5 million in revenues in Orbis.

Figure 14: Revenue and asset share of firms by age group (no revenue threshold)



**Notes:** The figures plot the share of revenues (left) and assets (right) accounted for by firms in four different age-groups: 0-5, 6-10, 11-20 and 21+. The shares are averages across two years during two different periods: 2013-14 and 2017-18. The sample is all manufacturing firms in Orbis.

## **E Additional Tables**



Table 4: Province-level young firm life-cycle growth vs. provincial SOE intensity

VARIABLES	(1)	(2)	(3)	(4)
	3-year revenue growth	3-year asset growth	3-year TFPQ growth	3-year intangibles' growth
State presence	-0.00950** (0.00439)	0.00420 (0.00440)	-0.00552** (0.00267)	-0.00131 (0.00661)
Constant	0.582*** (0.169)	-0.0226 (0.169)	0.303*** (0.103)	0.111 (0.261)
Observations	87	87	87	72
R-squared	0.477	0.471	0.542	0.554
Age	1-5	1-5	1-5	1-5
Years	2013-18	2013-18	2013-18	2013-18
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES

Notes: Table 4 reports results from province-year level regressions of the relative growth of young vs. old firms (in revenues, assets, TFPQ and intangibles) against province-year level measures of state presence. Young firms are those between the ages of 1 and 5, while older firms are those whose age is 16+. We include province and year fixed effects in all regressions.