Where Has All the Dynamism Gone? Productivity Growth in China's Manufacturing Sector, 1998-2013*

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Abstract

China's manufacturing sector has been a key source of the economy's dynamism. Analysis after 2007 however is hampered by problems in the key data source for empirical analysis, the National Bureau of Statistics' (NBS) annual survey of industrial firms. Issues include missing information on value added and intermediate inputs, and concerns of over-reporting. The annual survey of firms conducted by China's State Taxation Administration (STA) provides a reliable, alternative source of firm-level data for the years 2007 to 2013. Since the sample is not representative and the precise sampling scheme is not known, the data cannot be used directly to draw inferences on China's manufacturing sector. By comparing the joint distribution of key variables for which both surveys provide reasonably reliable information, we recover the sampling scheme of the STA survey and use it to simulate samples for 2007 to 2013 that are comparable to the NBS sample in earlier years. Our estimates reveal a marked slowdown in revenue-based total factor productivity growth that cuts across all industries, ownership types, and regions. The loss of dynamism in the private sector, and the reduced contribution of firm entry to aggregate productivity growth are especially prominent.

Keywords: TFP, Industrial development, Economic growth

JEL Classifications: D24, O14.

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1. Introduction

China's manufacturing sector has been an important source of the economy's dynamism and growth. Much of the analysis documenting the sector's contribution has focused on the period between 1998-2007 and used the National Bureau of Statistics (NBS) firm-level data. Analysis for later years is limited by data issues, most notably, missing data for several years after 2007, and data quality for the years for which we have data. Concerns of data quality parallel measurement issues at the macro level and indications that macro aggregates are inflated after 2007. Chen et al. (2019), for example, suggests over-reporting of annual GDP growth between 2010-2016 of 1.8 percent, with most of the over-reporting on the production side occurring in industry, and on the expenditure side in investment.[1] These problems likely originate with the NBS firm-level data that are used by the NBS in the construction of the national income accounts for China.

Over-reporting of GDP must be viewed in the context of work documenting falling GDP growth and an even sharper decline in TFP growth at the aggregate level after 2007 (e.g., Bai and Zhang 2017, Rajah and Leng 2022, Wu 2020). Analysis at the micro (firm) level is needed to confirm more aggregate estimates, and to identify the sources of the productivity slowdown. More generally, firm-level data are required to examine the effect of domestic policy shifts and changes in the external environment on firm behavior and performance. The micro data can also be used to provide estimates for key data moments for macro modeling and calibration.

In this paper, we leverage alternative firm-level data collected by the State Taxation Administration (STA) after 2007 to examine productivity and growth in the manufacturing sector between 1998 and 2013. We argue and document that reporting problems are much less severe in the STA data than in the NBS data.[2] Because many firms are sampled by both the NBS and the STA, we can directly compare their reported values. The key issue we face is that the STA sample is not representative; moreover, its sampling weights are unknown. We devise a methodology, based on Hellerstein and Imbens (1999), to draw simulated samples from the full STA sample that are similar in composition to the NBS sample and reflect the true firm population. We use these simulated samples to estimate industry-level production functions and firm-level productivity. The latter can be aggregated up to the sector and industry level and used to obtain estimates of aggregate productivity and productivity growth.

[1] Recent research suggests there are related problems in the reporting of agricultural output (Liu et al. 2020). The implications for NBS estimates of value added (GDP) in agriculture remain to be investigated.

[2] These data have been used in a number of influential studies, including Chen et al. (2021b) and Chen et al. (2023), which investigate the impacts of corporate income tax cuts on firms' R&D and the effects of the 2009 VAT reform on investment behavior.

We make the programs to draw simulated samples from the STA data publicly available to facilitate further use of this new data source.

Several key findings emerge. Over-reporting problems in the NBS micro data after 2007 parallel those identified at the macro level and become more serious over time. Utilizing the firm-level data from the STA, which does not suffer from this problem, we find significantly lower TFP growth after 2007 than before. Our preferred baseline estimates, which are likely to be an upper bound, suggest TFP growth of 1.1 percent between 2007-2013, less than a third of the growth rate between 1998-2007 estimated on the NBS data. This decline is observed across all industries, regions, and ownership types, but is especially prominent in China's private sector, which expanded the most over this period. Although some of this reduction occurs among incumbent firms, especially important is the disappearing contribution of new firm entry to aggregate productivity growth. The productivity level of newly entered firms falls significantly relative to that of incumbents. Data from the Business Registry further reveal a sharp drop in the rate of new firm entry over this period, especially by foreign-invested enterprises (FIE).

The remainder of the paper is organized as follows. In Section 2 we introduce and compare the two sources of firm-level data. In Section 3, we discuss the methodology to draw simulated samples from the original STA survey that are representative for the above-scale manufacturing sector. Section 4 covers the production function estimates and Section 5 the productivity results with breakdowns along several dimensions. Section 6 concludes and discusses several alternative explanations for the secular decline in productivity growth, which are worthy of future investigation.

2. Data

2.1 NBS Annual Survey of Above-scale Industrial Enterprises

China's National Bureau of Statistics (NBS) conducts an annual survey of mining, manufacturing and utility firms. Coverage has changed slightly over time. For 1998-2006, the survey covers *all* state-owned enterprises plus firms of all other ownership types with revenue larger than 5 million renminbi (RMB). The classification of firm ownership type is highly detailed, but we group them into four broad categories: state-owned firms (SOEs), other domestic Chinese firms (Non-SOEs), Hong Kong, Macau and Taiwan firms (HMT), and foreign-invested firms (FIEs). Beginning in 2007, ownership is dropped as a criterion and only firms with revenue exceeding 5 million RMB are included. In 2011, the minimum size threshold was raised to 20 million RMB. The 1998-2007 sample has been widely used in studies on the Chinese manufacturing sector.[3]

Brandt, Van Biesebroeck, and Zhang (2014) compares these data with firm censuses conducted in 1995, 2004 and 2008 and with aggregate information reported in China's Statistical Yearbooks. With few exceptions, these data aggregate almost perfectly to totals for the same set of variables reported in the Chinese Statistical Yearbook. Totals are also nearly identical to those for firms extracted from the 2004 Census that are either state-owned enterprises (SOEs) or non-SOEs with output value larger than 5 million. Comparison with the full census of firms reveals that 80% of all industrial firms are excluded from the NBS firm sample, but they represent only a small fraction of economic activity.[4]

After 2007, data issues make the NBS sample less credible and useful, especially if the objective is to compare results over time.[5] Value added, intermediate input use, and non-wage labor compensation are no longer reported. There are no data for 2010 and firms from several provinces are missing from the 2011 sample. Employment information for a majority of firms is identical in 2011 and 2012, and between 2012 and 2013 total manufacturing employment for firms in the sample increases by almost 50%. The values of key variables also appear to be over-reported on average, with important implications for China's national income accounts (Chen et al. 2019).

2.2 STA Annual Tax Survey

To monitor and facilitate tax collection, China's State Taxation Administration (STA) conducts an annual survey of firms covering both industry and the service sector. Listed companies, large private corporations and those affiliated with central or provincial governments are always surveyed. Two sampling schemes are used to select other firms. *Focus firms* are associated with special tax treatment and are

[3]Influential studies that primarily rely on the NBS Annual Survey of Above-scale Industrial Enterprises have investigated a wide range of economic issues: Hsieh and Klenow (2009) on misallocation; Lu and Tao (2009) on industrial agglomeration; Song, Storesletten, and Zilibotti (2011) on economic growth; Brandt, Van Biesebroeck, and Zhang (2012) on firm productivity; Hsieh and Song (2015) and Berkowitz, Ma, and Nishioka (2017) on state-owned enterprises; Yu (2015) on processing trade; Kee and Tang (2016) on global value chains; Lu and Yu (2015) and Brandt et al. (2017) on trade liberalization; Aghion et al. (2015) on industrial policy; Hau, Huang, and Wang (2020) on minimum wage; He, Wang, and Zhang (2020) and Fu, Viard, and Zhang (2021) on pollution; Whited and Zhao (2021) on firm finance; and Imbert et al. (2022) on internal migration.

[4]In 2004, below-scale firms employed 28.8% of workers in industry, but produced only 9.9% of output and generated 2.5% of exports.

[5]Some of these problems originate earlier than previously believed. In Section 5.3, we examine the most serious of these issues: inflated values in the firm-level data for value added. These problems may help explain why value added and intermediate input use are no longer reported in the NBS firm-level data from 2008 onward. We also examine the sensitivity of our productivity estimates to these concerns.

always included.[6] *Sampled firms* are selected from the universe of all remaining active firms using a stratified sampling scheme. During the 2007-2013 sample period, they constitute the majority of the sample, e.g. 80 percent of all firms in 2007.[7] The STA provides detailed guidelines regarding the sampling scheme. The strata are based on 2-digit industry and firm size, with categories for small, medium and large firms defined by revenue cutoffs of 20 and 400 million RMB, respectively. The relative sizes of the different strata do not correspond to their relative importance in the economy.

Once the State Tax Administration has drawn a sample of firms, implementation of the survey is delegated to local offices. Sample replacement is allowed and should be recorded. The effective sampling weight for each strata is subject to further adjustment by local offices to save on costs, to guarantee better coverage in terms of collected taxes, and to fit industry-level statistics.[8] As a result, the STA survey produces a sample that is unrepresentative of the population of Chinese non-agriculture firms and for which the exact sampling weights are unknown. Moreover, firms that enter or exit the sample do not necessarily enter or exit the economy.

China's STA data are less sensitive to local political influences, but are subject to other reporting biases related to their role in tax administration. This is easiest to see in the case of the VAT, which was the source of more than 47 percent of China's total government fiscal revenue at its peak in 2002 (Fan et al. 2020). Under China's VAT, a common form of tax evasion is to use falsified invoices for input purchases. This allows firms to obtain larger VAT deductions, but implies an over-reporting of firms' intermediate input use in the STA data. Firms also have incentives to hide sales from the tax bureau to avoid paying the VAT, which might result in an under-reporting of revenue in the STA data.[9]

There are several channels through which errors in the STA data may affect our primary object of interest, productivity. In growth accounting, productivity estimates are the residual obtained from subtracting contributions of input growth from output growth. Thus, biases in measures of input and output growth directly affect TFP

[6] Firms receiving special tax treatment include major taxpayers, processing exporters under special customs' regulation, firms receiving a reduction in value-added tax (VAT), foreign-invested firms, exporters that pay VAT, and listed firms with a major business subject to VAT.

[7] Although we have access to the STA data up to 2015, we do not use the last two years (2014 and 2015) in the analysis for two reasons. First, our NBS sample only runs to 2013. It is difficult to simulate samples from the STA without the corresponding NBS sample. Second, the sampling frame for the STA data changed between 2013 and 2014, with only 40 percent of the firms in the 2013 STA data sampled again in 2014.

[8] For example, documents detailing the organization of the 2008 and 2011 surveys indicate that all surveyed firms combined need to account for 70% of VAT revenue and 85% of consumption tax revenue. For more detailed information on the survey implementation in 2015, see http://www.mof.gov.cn/gkml/caizhengwengao/wg2015/wg201506/201511/t20151120_1574220.htm.

[9] This problem is less common than input invoice falsification as downstream buyers that pay VAT require proper invoices for deduction purpose. Moving an entire value chain to off-book cash transactions involves coordination among firms and is costly.

growth estimates. In addition, errors in the levels of the same variables may have an indirect impact through biasing the output elasticity estimates which determine the weight on each input growth.

As for their direct impact on measured TFP growth, only the trend of these biases matter. Here we have reasons to believe that the under-reporting of revenue and over-reporting of inputs has lessened over time. Since 2007, the STA has carried out a series of reforms to make the VAT system less distortionary and more transparent to facilitate tax collection.[10] As a result, our estimates based on the STA data likely under-estimate the growth rate of intermediate inputs and over-estimate the growth rate of gross output. For a given set of production function parameters, this implies an overestimation of the TFP growth rate. Therefore, we consider our TFP growth estimates for 2007-2013 based on the STA data to be an upper bound for true TFP growth.

In Section 5.3 we evaluate one potential channel through which measurement issues in the STA can impact productivity estimates, namely through biased estimates of the output elasticities. We calculate TFP growth twice for each of the periods, 1998-2007 and 2007-2013, using the production technology estimated on either of the sub-periods. The aggregate TFP growth estimate is not sensitive at all to the technology.

2.3 Comparison of the NBS and STA samples

We retain manufacturing firms from the two surveys and summarize their coverage and overlap in Table 1. The NBS survey samples many more firms, but the difference narrows with the increase in the size threshold of the NBS survey to 20 million RMB in 2011. There are also marked differences in the size distribution of firms: almost all of the firms in the NBS sample are above-scale, but only half of the firms in the STA sample exceed the same size threshold. In addition, the share of firms "new to the sample" is significantly higher in the STA sample, reflecting the rotation in its sampling scheme.

Nonetheless, between one-third to one-half of firms from one sample also appear in the other sample in any given year. The last column of Table 1 implies that the vast majority of above-scale firms in the STA can be matched to observations in the NBS sample on the basis of firms' names and legal ID, with this fraction exceeding 80% the last three years.[11]

To evaluate the consistency of the reported information in the two surveys, we calculate for key variables for matched firms the ratio of the value reported in the STA

[10] Included in these reforms are: (1) computerization of the VAT invoice system; (2) inclusion of capital goods in the VAT deductible input purchase (2009); and (3) conversion of the business tax system to the VAT system in the service sector (2012).

[11] In 2013, for example, (51-9.5)/51 = 81.4 percent of firms can be matched.

Table 1: Coverage of the NBS and STA samples

Year	(a) NBS survey No. of firms	Above scale (%)	New in sample (%)	Matched w/ STA (%)	(b) STA survey No. of firms	Above scale (%)	New in sample (%)	Matched w/NBS (%)	Above & Unmatched (%)
2007	312,055	98.1	18.2	35.5	269,659	41.2	-	41.2	11.6
2008	382,813	97.8	29.0	34.8	306,985	45.1	28.7	43.5	11.5
2009	361,720	98.3	8.8	36.0	302,515	50.4	29.8	43.3	16.7
2010	-	-	-	-	309,815	56.3	36.4	-	-
2011	279,242	98.6	-	45.5	279,666	44.5	25.6	45.5	9.5
2012	288,627	98.3	12.8	44.0	255,689	50.3	28.2	49.8	11.0
2013	319,673	98.7	18.3	41.4	246,655	51.0	20.7	53.7	9.5

Notes: Observations are matched by name and legal entity ID (组织机构代码、法人代码). The "above-scale" cutoff rises from 5 million to 20 million RMB in 2011.

survey to the value in the NBS survey. If firms report identical information in the two surveys, the ratio will be one. A value below (above) one indicates higher (lower) reported values in the NBS sample. Table 2 reports percentiles from the distribution of these ratios.

Differences in reporting between the surveys are most evident in the case of output and employment. While the median ratio for the two variables was 1.00 in 2007, the ratios at almost all percentiles decline notably over time, indicative of an increase in over-reporting in the NBS data. The decline is especially noticeable for firms in the lower tail of the ratio distribution. For example, for output (employment), the ratio at the 25th percentile declines from 0.54 (0.81) in 2007 to 0.26 (0.36) in 2013. Note also that for both variables, the ratios at the 90th percentile are above one, indicating that more than ten percent of firms report larger values in the STA survey.

Information on paid-in (registered) capital is most consistently reported, with more than two-thirds of matched firms typically having identical values in both surveys. The data also match reasonably well for fixed assets at original purchase price, especially for the median and higher percentiles. The 25th percentile is close to one in 2007, but falls to 0.69 by 2013. Other variables that we will use to construct sample weights are reported in panels (e) to (h). The ratios are even closer to 1.00 for reported firm age than for paid-in capital; export value is also measured very consistently in the two samples. Differences are slightly larger for export status and the total wage bill, but the discrepancies are smaller than either for output or employment.

To investigate the pattern in reporting differences, we plot in Figure 1 the coefficients from OLS regressions of the log differences in the values reported in the two surveys for firm output and paid-in capital on a set of dummy variables for province, ownership type and 2-digit industry. Along each dimension we pick

Table 2: **Ratios of reported values in the matched NBS-STA sample**

Year	(a) Output					(b) Employment				
	p10	p25	p50	p75	p90	p10	p25	p50	p75	p90
2007	0.14	0.54	1.00	1.00	1.08	0.43	0.81	1.00	1.05	1.33
2008	0.12	0.47	0.97	1.00	1.05	0.40	0.77	1.00	1.04	1.28
2009	0.08	0.32	0.88	1.00	1.15	0.35	0.75	1.00	1.05	1.40
2011	0.09	0.30	0.88	1.00	1.04	0.19	0.36	0.62	0.88	1.29
2012	0.09	0.32	0.91	1.00	1.04	0.19	0.36	0.60	0.87	1.43
2013	0.07	0.26	0.86	1.00	1.04	0.18	0.36	0.67	1.13	1.77
	(c) Paid-in Capital					(d) Fixed Assets				
	p10	p25	p50	p75	p90	p10	p25	p50	p75	p90
2007	0.50	1.00	1.00	1.00	1.03	0.36	0.97	1.00	1.00	1.04
2008	0.46	1.00	1.00	1.00	1.00	0.24	0.84	1.00	1.00	1.01
2009	-	-	-	-	-	-	-	-	-	-
2011	0.50	1.00	1.00	1.00	1.12	0.18	0.68	1.00	1.00	1.04
2012	0.60	1.00	1.00	1.00	1.00	0.19	0.78	1.00	1.00	1.02
2013	0.50	1.00	1.00	1.00	1.02	0.16	0.69	1.00	1.00	1.02
	(e) Export value					(f) Number of Exporters				
	p10	p25	p50	p75	p90	NTB		STA		BOTH
2007	0.28	0.78	1.00	1.02	1.21	34,226		34,709		27,680
2008	0.16	0.65	1.00	1.01	1.25	38,878		34,423		24,873
2009	0.19	0.69	1.00	1.01	1.21	36,043		39,614		27,923
2011	0.26	0.87	1.00	1.01	1.20	38,412		45,073		33,056
2012	0.30	0.88	1.00	1.01	1.18	42,032		50,012		37,781
2013	0.27	0.87	1.00	1.01	1.19	40,550		49,173		36,126
	(g) Firm age					(h) Wage				
	p10	p25	p50	p75	p90	p10	p25	p50	p75	p90
2007	0.62	1.00	1.00	1.00	1.38	0.25	0.63	1.00	1.02	1.30
2008	0.75	1.00	1.00	1.00	1.33	0.18	0.50	0.98	1.00	1.23
2009	0.75	1.00	1.00	1.00	1.56	-	-	-	-	-
2011	0.82	1.00	1.00	1.00	1.17	0.17	0.49	0.91	1.00	1.25
2012	0.86	1.00	1.00	1.00	1.17	0.19	0.52	0.91	1.00	1.21
2013	0.88	1.00	1.00	1.00	1.12	0.16	0.47	0.86	1.00	1.18

Notes: Reported statistics are the ratio of the values for the same variable in both samples: (STA value)/(NBS value). Information on Paid-in Capital and the value of Fixed Assets at original purchase price is not reported in the 2009 NBS survey. Panel (f) presents the count of exporters with reported export value above 10,000 RMB in each sample and the number of those firms reported as exporters in both samples.

a reference category that has one of the lowest reporting discrepancies: Shanghai for province, foreign-invested firms for ownership type, and China Industrial Classification (CIC) industry 37, which is Transportation Equipment.

Panel (a) shows provincial differences and Panel (b) shows differences across ownership types. The regressions are run separately for each year, but we only show the estimates for 2007 and 2013 in Panel (a), and 2007, 2011, and 2013 in Panel (b). The intercepts, which are the average discrepancies for a foreign firm in CIC industry 37 based in Shanghai, are 0.110 and -0.079 for paid-in capital in 2007 and 2013, respectively, and -0.051 and 0.035 for output. Especially for output, much of the discrepancies can be explained by the observables.[12]

Several patterns emerge. First, there are marked geographic differences, with over-reporting in output much more severe in provinces in the northeast and central China. The gap in Beijing, Shanghai, Jiangsu, Zhejiang and Guangdong, five of the highest per capita GDP provinces, is much smaller and in the vicinity of 10%. Second, over-reporting widens most in those provinces where it was already more severe in 2007. For example, in Liaoning it rises from 20% in 2007 to 140% in 2013, and in Jilin from 40% to 140%. And third, over-reporting is endemic to all ownership types, but several times more serious in the case of non-SOE, i.e. mostly private, firms. Overall, the spatial dimensions of over-reporting at the micro-level line up well with a forensic examination of related reporting issues in province-level industry GDP (Chen et al. 2019), which identified a similar set of provinces as problematic.[13] The fact that the NBS annual firm survey data are used in the construction of GDP estimates for industry in the National Income Accounts provides a direct link between the problems.

3. Correcting for the STA survey sampling

Our comparison of the two samples implies that we cannot evaluate the productivity evolution of China's manufacturing sector after 2007 using either the NBS sample or the STA sample alone. Crucial variables are missing and the reported values in the NBS sample are systematically biased for others, while the STA sample is unrepresentative of the entire manufacturing sector.

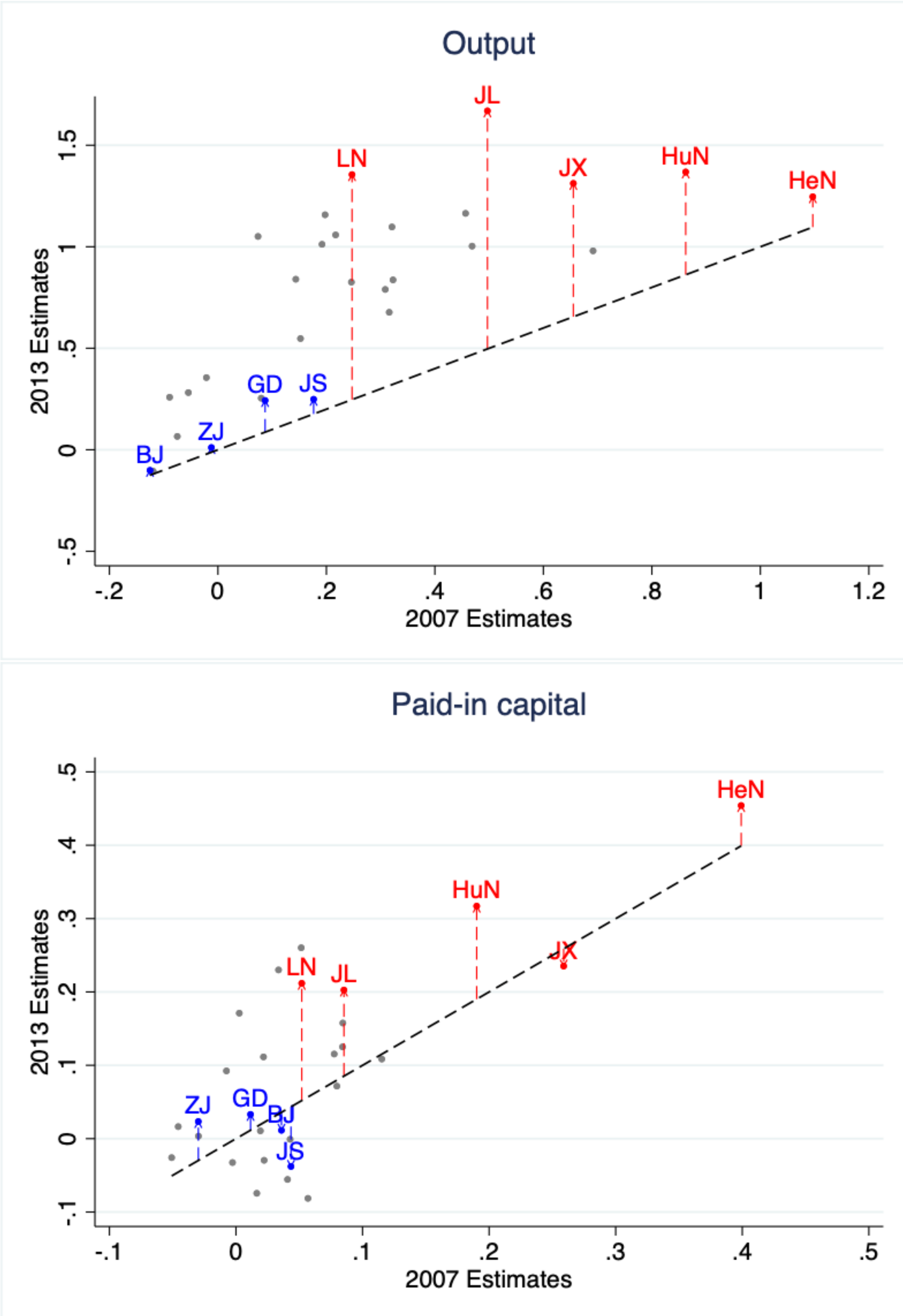
To correct for these issues, we follow the approach of Hellerstein and Imbens (1999) and use information on several well-reported variables from the NBS target sample, which is representative of the population, to weight observations in the STA source sample such that the resulting sample is both reliable and representative. We construct two possible weighting functions, a *time-invariant* function that only relies on observing the target NBS population in a single year, 2007, and a *time-varying* function that requires several variables that are reported accurately in the NBS sample

[12]The patterns are similar on the matched sample of firms appearing in both the NBS and STA data in both 2007 and 2013, a total of 24,128 firms. The discrepancy in output rises from 22% to 39% and for paid-in capital from 4% to 10%. Restricting the sample to firms located in Shanghai (940 firms), the output discrepancy is consistently 5% and increases slightly for paid-in capital from 1% to 2%. For a matched balanced sample of foreign invested firms (3,966 firms), the total output discrepancy rises from 12% to 22%, and for paid-in capital from 0 to 4%.

[13]Over-reporting of agricultural output in an overlapping set of provinces suggests a common set of forces at work (Liu et al. 2020).

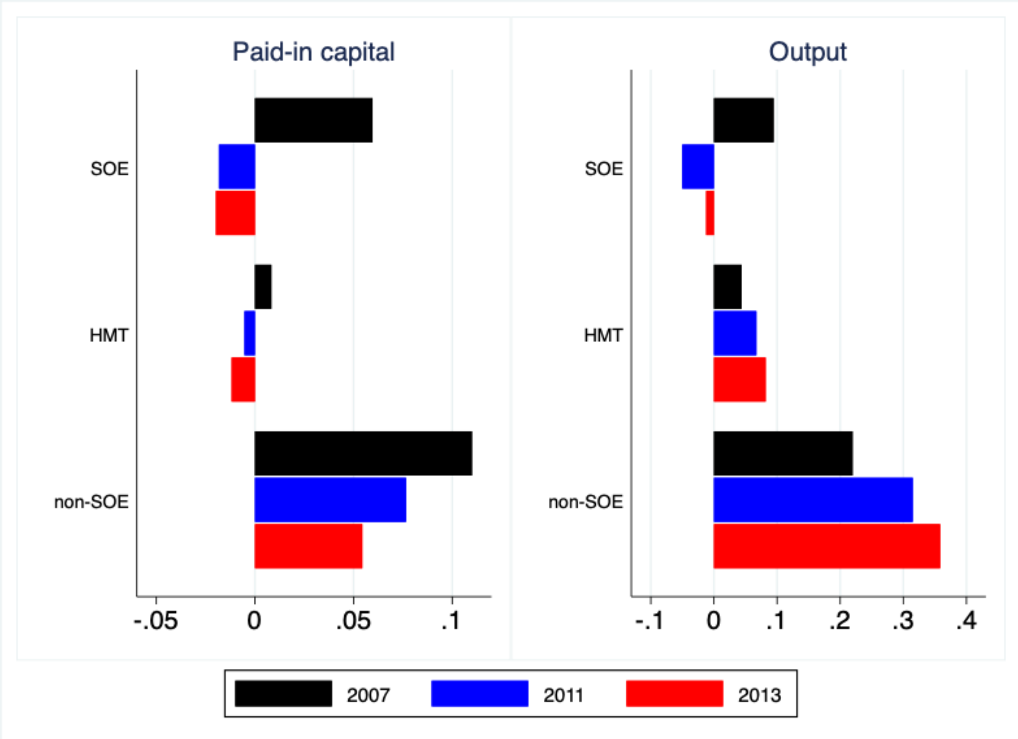
Figure 1: Patterns in the reporting discrepancies

(a) Discrepancy by province



Notes: Discrepancy measures are obtained as coefficients on province dummies (Shanghai as reference) from annual regressions of the reporting discrepancy on firm characteristics that further include 2-digit industry-fixed effects and ownership type indicators. Each marker represents a province in mainland China. Arrows indicate the difference from the 45 degree line, i.e., the change in discrepancy from 2007 to 2013 relative to the change recorded for Shanghai. Provinces in blue (BJ-Beijing, ZJ-Zhejiang, GD-Guangdong, JS-Jiangsu) consistently show a low output discrepancy; provinces in red (LN-Liaoning, JL-Jilin, HuN-Hunan, JX-Jiangxi, HeN-Henan) either have very high discrepancy by 2013 or experienced a very large increase in discrepancy between 2007 and 2013.

(b) Discrepancy by ownership type



Notes: Discrepancy measures are obtained as coefficients on ownership type dummies (foreign-invested firms as reference) from annual regressions of the reporting discrepancy on firm characteristics that further include 2-digit industry-fixed effects and province indicators.

also in later years. We can then construct a weighting factor based on the discrepancy between the distributions of those variables in the two samples. The time-varying is more appropriate if the sampling scheme of the source data changes over time, which it likely does.

We first describe how the implicit sampling weights relate to the ratio of joint densities of input and output variables from the two samples. This density ratio is the inverse of the conditional probability of being sampled in the STA. Next, we discuss the approach of Kanamori, Hido, and Sugiyama (2009) to estimate the density ratio, which we will use to simulate samples for years after 2007. Finally, we compare the marginal distributions of key variables in the NBS, STA and simulated samples, which helps validate the procedure.

3.1 Sampling weights and density ratio

We want to estimate the size-weighted average productivity for a particular industry and sample of interest, which we refer to as the target sample T. We observe the following variables on a source sample S: (1) firm-level output (y); (2) a vector of inputs ($\mathbf{x}$) and (3) a vector of firm attributes ($\mathbf{A}$) that are relevant to productivity. Productivity ω^* is defined as the residual output after taking out the contribution of inputs $s(\mathbf{x};\theta)$, with θ a vector of parameters governing the common part of the production technology.

For a given θ and production function, a firm's productivity can be represented by the function $g(y, \mathbf{x}, \mathbf{A})$. The moment of interest, the size-weighted aggregate productivity, depends on the joint distribution of output, inputs and productivity shifters:

$$
\begin{aligned}
m_t^T(\mathbf{y}, \omega^*(\mathbf{A})) &= m_t^T(\mathbf{y}, \mathbf{y} - \mathbf{s}(\mathbf{x}; \theta) + \mathbf{h}(\mathbf{A})) \\
&= \int_y \int_{\mathbf{x}} \int_{\mathbf{A}} g(y, \mathbf{x}, \mathbf{A}) f_t^T(y, \mathbf{x}, \mathbf{A})\, d_{\mathbf{A}} d_{\mathbf{x}} d_y, \qquad (1)
\end{aligned}
$$

where $\mathbf{h}(\mathbf{A})$ captures how attributes shift productivity and $f_t^T(y, \mathbf{x}, \mathbf{A})$ denotes the joint density of the output, input and attribute variables in the target sample.

Given that we do not observe the target sample in later years, we multiply and divide by the source sample density f_t^S and express this moment equivalently as:

$$
m_t^T(\mathbf{y}, \omega^*(\mathbf{A})) = \int_y \int_{\mathbf{x}} \int_{\mathbf{A}} g(y, \mathbf{x}, \mathbf{A})\, r_t(y, \mathbf{x}, \mathbf{A}) f_t^S(y, \mathbf{x}, \mathbf{A})\, d_{\mathbf{A}} d_{\mathbf{x}} d_y, \qquad (2)
$$

where

$$
r_t(y, \mathbf{x}, \mathbf{A}) = \frac{f_t^T(y, \mathbf{x}, \mathbf{A})}{f_t^S(y, \mathbf{x}, \mathbf{A})}. \qquad (3)
$$

To draw inferences for the target sample T, observations in the source sample S are weighted by the density ratio r_t to adjust for the difference in sample composition.

Both $g(y, \mathbf{x}, \mathbf{A})$ and $f_t^S(y, \mathbf{x}, \mathbf{A})$ can be calculated from the source sample. However, because we do not observe $(y, \mathbf{x}, \mathbf{A})$ for the target sample in later years, we cannot calculate $r_t(y, \mathbf{x}, \mathbf{A})$ year by year. We obtain two estimates of this density ratio that are valid under alternative assumptions regarding the STA sampling scheme. If the STA sampling scheme remains unchanged over time, we can use a *time-invariant* or constant density ratio function $r_{2007}(y, \mathbf{x}, \mathbf{A})$ that is estimated using 2007 data for both samples. All functions in equation (2) are then observed and it can be implemented directly.

If the sampling scheme changes over time, we need a *time-varying* density ratio function. In that case, we require an additional assumption to avoid using the output variable y_t from the target distribution in later years. We assume that we observe variables $(k, \mathbf{z}, \mathbf{A})$—defined below—that predict the probability of appearing in the source sample in the same way as variables $(y, \mathbf{x}, \mathbf{A})$, i.e.,

$$
Prob_t(S = 1 | y, \mathbf{x}, \mathbf{A}) = Prob_t(S = 1 | k, \mathbf{z}, \mathbf{A}). \qquad (4)
$$

We can use Bayes' law to relate the source density to the target density[14]

$$f_t^S(y,\mathbf{x},\mathbf{A}) \;=\; f_t^T(y,\mathbf{x},\mathbf{A}|S=1) \;=\; \frac{Prob(S=1|y,\mathbf{x},\mathbf{A})f_t^T(y,\mathbf{x},\mathbf{A})}{Prob(S=1)}.$$

A similar equation applies conditioning on the $(k,\mathbf{z},\mathbf{A})$ variables, such that we can rewrite both density ratios as

$$\frac{f_t^S(y,\mathbf{x},\mathbf{A})}{f_t^T(y,\mathbf{x},\mathbf{A})} = \frac{Prob(S=1|y,\mathbf{x},\mathbf{A})}{Prob(S=1)} \quad \text{and} \quad \frac{f_t^S(k,\mathbf{z},\mathbf{A})}{f_t^T(k,\mathbf{z},\mathbf{A})} = \frac{Prob(S=1|k,\mathbf{z},\mathbf{A})}{Prob(S=1)}.$$

Assumption (4) then implies that the target density ratio can be expressed in two equivalent ways, i.e., that $r_t(y,\mathbf{x},\mathbf{A}) = r_t(k,\mathbf{z},\mathbf{A})$. If we observe the density of variables $(k,\mathbf{z},\mathbf{A})$ in both the target and source samples in all years, the alternative density ratio can be used to estimate aggregate productivity from

$$m_t^T(y,\omega^*(\mathbf{A})) \;=\; \int_y\int_{\mathbf{x}}\int_{\mathbf{A}} g(y,\mathbf{x},\mathbf{A})\, r_t(k,\mathbf{z};\mathbf{A}) f_t^S(y,\mathbf{x},\mathbf{A})\, d_{\mathbf{A}} d_{\mathbf{x}} d_y. \tag{5}$$

We can estimate the same object, i.e., the size-weighted average productivity conditional on attributes $\mathbf{A}=\mathbf{a}$, only for a subgroup of firms. We rely on the same ratio of unconditional densities, but also need to adjust for the relative frequency of the subgroup in the two samples. The productivity for the subgroup is then:

$$\begin{aligned}
m_t^T(y,\omega^*(\mathbf{A})|\mathbf{A}{=}\mathbf{a}) &= \int_y\int_{\mathbf{x}} g(y,\mathbf{x},\mathbf{a})\,\frac{f^T(y,\mathbf{x},\mathbf{a})}{Prob^T(\mathbf{A}=\mathbf{a})}\, d_{\mathbf{x}} d_y \\
&= \int_y\int_{\mathbf{x}} g(y,\mathbf{x},\mathbf{a})\,\frac{r_t(k,\mathbf{z},\mathbf{a}) f^S(y,\mathbf{x},\mathbf{a})}{Prob^T(\mathbf{A}=\mathbf{a})}\, d_{\mathbf{x}} d_y \\
&= \int_y\int_{\mathbf{x}} g(y,\mathbf{x},\mathbf{a})\, r_t(k,\mathbf{z},\mathbf{a})\,\frac{Prob^S(\mathbf{A}=\mathbf{a})}{Prob^T(\mathbf{A}=\mathbf{a})} f^S(y,\mathbf{x},\mathbf{A}|\mathbf{A}=\mathbf{a})\, d_{\mathbf{x}} d_y. \qquad (6)
\end{aligned}$$

3.2 Estimating the density ratio

To implement the aggregation in equations (2) or (5), we need to estimate either $r_{2007}(y,\mathbf{x})$ or $r_t(k,\mathbf{z})$. We use the Least Squares Importance Fitting method of Kanamori, Hido, and Sugiyama (2009).

Denote the true density-ratio function that we want by $r^*(\mathbf{v}) = f^{T^*}(\mathbf{v})/f^{S^*}(\mathbf{v})$ with $\mathbf{v}$ representing $(y,\mathbf{x})$ or $(k,\mathbf{z})$ for either density ratio approach. The estimate will

[14]Note that we only apply this methodology to above-scale firms, hence the first equality is only assumed for them. In principle, if the NBS was a true census, this assumption would be satisfied automatically. In practice, there are above-scale firms in the STA sample that do not appear in the NBS sample, i.e., the "Above & Unmatched" firms in the last column of Table 1. We assume that they have the same joint density of $(y,\mathbf{x},\mathbf{A})$ as NBS firms.

be the function $r(\cdot)$ that minimizes the squared error

$$\begin{aligned} SQ(r) &\equiv \frac{1}{2}\int_{\mathbf{v}} \left(r(\mathbf{v}) - r^*(\mathbf{v})\right)^2 f^{S^*}(\mathbf{v})d\mathbf{v} \\ &= \frac{1}{2}\int_{\mathbf{v}} r(\mathbf{v})^2 f^{S^*}(\mathbf{v})d\mathbf{v} - \int_{\mathbf{v}} r(\mathbf{v}) f^{T^*}(\mathbf{v})d\mathbf{v} + \frac{1}{2}\int_{\mathbf{v}} r^*(\mathbf{v})^2 f^{S^*}(\mathbf{v})d\mathbf{v}. \end{aligned}$$

The last term is a constant, while the empirical counterpart to the first two terms is

$$\widehat{SQ}(r) = \frac{1}{2n^S}\sum_{i=1}^{n^S} r(\mathbf{v}_i^S)^2 - \frac{1}{n^T}\sum_{j=1}^{n^T} r(\mathbf{v}_j^T).$$

We approximate the density ratio function by a linear expression $\sum_{c=1}^{C}\alpha_c\phi_c(\mathbf{v})$, where $\{\phi_c(\mathbf{v})\}_{c=1}^{C}$ are basis functions capturing distance of point $\mathbf{v}$ to each of the C kernel centers and $\alpha' = (\alpha_1, \alpha_2, ..., \alpha_C)$ are combination weights to be estimated. Using this expression in $\widehat{SQ}(r)$ gives

$$\widehat{SQ}(\alpha) = \frac{1}{2}\sum_{c=1}^{C}\sum_{c'=1}^{C}\alpha_c\alpha_{c'}\left(\frac{1}{n^S}\sum_{i=1}^{n^S}\phi_c(\mathbf{v}_i^S)\phi_{c'}(\mathbf{v}_i^S)\right) - \sum_{c=1}^{C}\alpha_c\left(\frac{1}{n^T}\sum_{j=1}^{n^T}\phi_c(\mathbf{v}_j^T)\right).$$

Collecting all the terms in brackets into matrices, the estimation effectively becomes the following optimization problem:

$$\min_{\alpha\in\mathcal{R}^C}\left[\frac{1}{2}\alpha'\widehat{H}\alpha - \widehat{h}'\alpha + \lambda\mathbf{1}_C'\alpha\right] \qquad \text{subject to } \alpha \geq \mathbf{0}_C,$$

where matrix $\widehat{H}$ has dimensions $C \times C$ with $\frac{1}{n^S}\sum_{i=1}^{n^S}\phi_c(\mathbf{v}_i^S)\phi_{c'}(\mathbf{v}_i^S)$ as element in cell (c, c'); vector $\widehat{h}$ has length C with $\frac{1}{n^T}\sum_{j=1}^{n^T}\phi_c(\mathbf{v}_j^T)$ in row c; and $\lambda \geq 0$ is a regularization parameter.

Kanamori, Hido, and Sugiyama (2009) proposes a more practical version of the algorithm which ignores the non-negativity constraint and replaces the linear regularization term with a quadratic one. The unconstrained optimization problem is

$$\min_{\beta\in\mathcal{R}^b}\left[\frac{1}{2}\beta'\widehat{H}\beta - \widehat{h}'\beta + \frac{\lambda}{2}\beta'\beta\right],$$

which can be solved as a system of linear equations. The solution takes the form

$$\widehat{\beta}(\lambda) = \max\left(\mathbf{0}_C, \widetilde{\beta}(\lambda)\right) \text{ with } \widetilde{\beta}(\lambda) = \left(\widehat{H} + \lambda I_C\right)^{-1}\widehat{h},$$

where I_C is a $C \times C$ identity matrix and the max-operation is implemented point-wise.

3.3 Implementation

3.3.1 Estimating the sampling weights

We first estimate the density ratio function, which acts as a weighting function to draw simulated samples from the STA that reflect the target NBS firm population. In principle, we could estimate a single density ratio function to cover all sizes of firms. Ideally, however, the ratio is estimated separately for each of the three strata of the STA survey, i.e., firms with output between 5-20 million, 20-400 million, and more than 400 million RMB. The simulated sample will fit the target sample better when we apply our prior knowledge about the STA's sampling scheme. Doing so also reduces the computational burden.

The time-invariant density ratio, $r_{2007}(y, \mathbf{x}, \mathbf{A})$, takes as arguments the output and input variables used in the productivity estimation, as well as firm attributes that are potential productivity shifters, including region, ownership type, and firm age, and uses only information from 2007 for both the source (STA) and target (NBS) samples.

The estimation of the time-varying density ratio function retains the data on the real capital stock k from $\mathbf{x}$, which is calculated for each year in the two samples and shows relatively small differences between the two surveys. It replaces y and other input variables in $\mathbf{x}$ with $\mathbf{z}$, a vector of consistently measured firm-level variables that do not directly enter the production function, namely, the wage bill, fixed assets at original purchase price, paid-in capital, export status and export value.

We use Gaussian kernels for the basis functions $\phi(\cdot)$ and take 1000 Gaussian centers $\mathbf{c}$ from the combination of $\mathbf{v}^S$ and $\mathbf{v}^T$.[15] In the time-invariant density function, we estimate combination weights β with the 2007 data and apply the same function to construct the weights for STA observations of all subsequent years. In the time-varying density function, we estimate combination weights β for each year separately and construct weights for STA observations using the year-specific weights.

3.3.2 Data issues

For the time-invariant case, we are able to estimate separate density ratio functions for each of the three firm-size strata. Several data shortcomings require modifications in how we implement the time-varying weighting scheme. First, the size threshold for inclusion in the NBS survey was raised from 5 to 20 million RMB in 2011. Without data on firms with output values between 5 and 20 million RMB for these years, we cannot estimate separate density ratio functions for all three groups. Second, since

[15] Therefore $\widehat{r}(\mathbf{v}) = \sum_{l=1}^{1000} \alpha_l K_\sigma(\mathbf{v}, \mathbf{c}_l)$ with $K_\sigma(\mathbf{v}, \mathbf{v}') = \exp\left(-||\mathbf{v} - \mathbf{v}'||^2/(2\sigma^2)\right)$ with σ the kernel width. Tuning parameters σ and λ will be determined by leave-one-out cross-validation through grid search within the range of $(1/6, 6)$ for both parameters.

output information in the NBS survey becomes less accurate over time, we cannot reliably split the NBS sample into (output) size categories to match the stratified sampling scheme by STA for later years. Finally, the NBS survey for 2009 does not report information on paid-in capital, fixed assets at original purchase price, and the wage bill, while no NBS sample is available for 2010.

Our strategy is to estimate for each year that we have data a weighting function based on the full NBS sample and the subset of firms in the STA sample with revenue above 20 million RMB and use it to simulate the sample above 20 million RMB. For firms with sales between 5-20 million RMB, we apply the 2007 weighting function for this size category in other years. Since we cannot estimate a separate weighting function for 2009 and 2010, we apply the weighting function estimated on 2008 data to the STA data for these two years.

3.3.3 Size of simulated samples

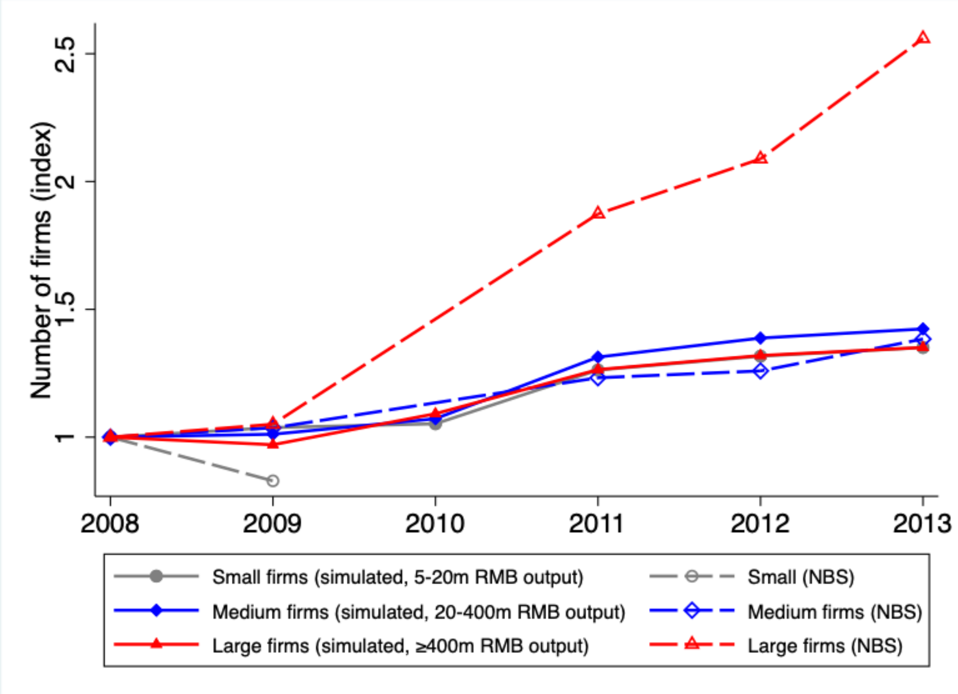
The estimated density ratios provide sampling weights that we use to simulate samples from the STA source data by industry and firm-size category with the same composition as the NBS sample. We still need to determine how many firms to sample given that the Chinese manufacturing sector grows over time. The annual NBS Statistical Yearbooks report the number of above-scale firms by industry in each year. One shortcoming of this data source is that after 2010 it no longer reports information on firms with output values between 5-20 million RMB. Moreover, inflated values for firm output may bias the breakdown over the three size categories.

We leverage the Business Registry of the State Administration for Industry and Commerce (SAIC) and the annual Inspection Data to determine for each year the active number of firms in each of the three size categories.[16] Our starting point is the number of firms in each size category in the NBS data for 2008, a year in which the Enterprise Census was carried out. From the Business Registry and Inspection Data, we can estimate the growth of firms in each size category between 2008-2013. We apply these growth rates to the number of firms in 2008 to obtain the size breakdown for all other years. The total number of firms in each size category is then determined by applying the estimated size breakdown to the total number of above-scale firms reported in the NBS Statistical Yearbook.

Figure 2 reports the growth in the number of firms by size category in both the original NBS data (dashed lines) and the alternative estimates that we use (solid lines). Between 2008 and 2013, the NBS data shows an implausibly large increase in the number of large firms (with output values above 400 million RMB). By comparison,

[16]For regulatory purposes, SAIC collects annual information on all firms' assets, liabilities, total sales, output values, total profit, net profit, and total taxes. We refer to these data as the Inspection Data.

Figure 2: Evolution of the number of firms by size category



Notes: All lines represent an index (2008=1) for the evolution of the number of firms in three size categories. The solid lines are the numbers used to simulated the samples from the STA, and are predicted based on three data sources (see text). The dashed lines show the evolution of the number of firms in the NBS sample.

our alternative estimates suggest similar rates of growth in the number of firms across all three size categories. As shown in Table A.1 in the Appendix, by 2013 the number of large firms in the NBS sample is 70% higher than the estimates we obtain.

3.3.4 Sample simulation

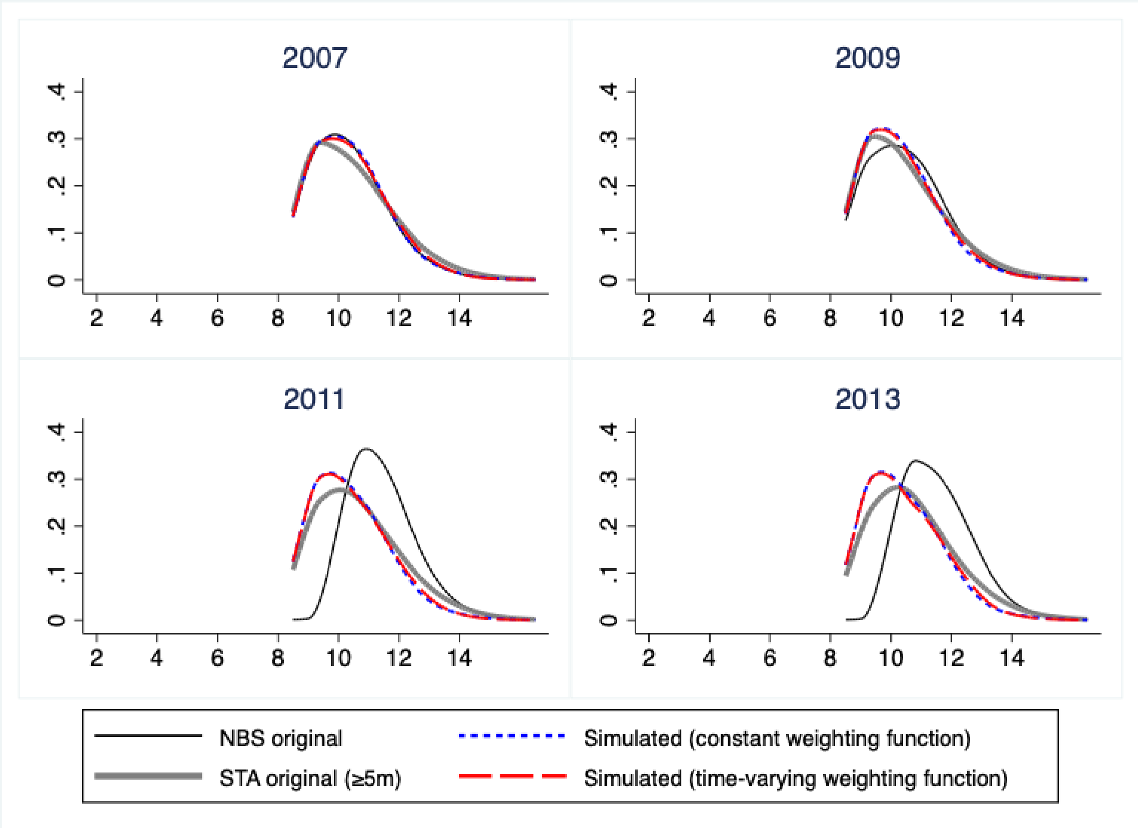
We simulate 5 samples from the STA survey and perform all subsequent analyses on each sample, reporting the average results. For each year and industry-size category, we put the observations from the STA survey into 10 equal-sized bins based on the estimated firm-specific weights discussed in Section 3.3.1. The sum of these weights in each bin determines the fraction of firms in each simulated sample that should come from that bin. The absolute number of firms to simulate was already discussed.

Panel (a) of Figure 3 shows the non-parametrically fitted densities of log output for four years. Panel (b) shows the same for the log of paid-in capital. Each line represents the density for a different sample: the NBS sample (black), the original STA sample (gray), but keeping only firms with annual output above 5 million RMB, and the two simulated samples using either constant (blue) or time-varying (red) weighting schemes.

The sampling weights that we employ are able to generate samples that achieve two things at the same time. First, in contrast to the output density for the NBS

Figure 3: Marginal distributions of selected variables in the different samples

(a) Kernel density of (log) output



(b) Kernel density of (log) paid-in capital

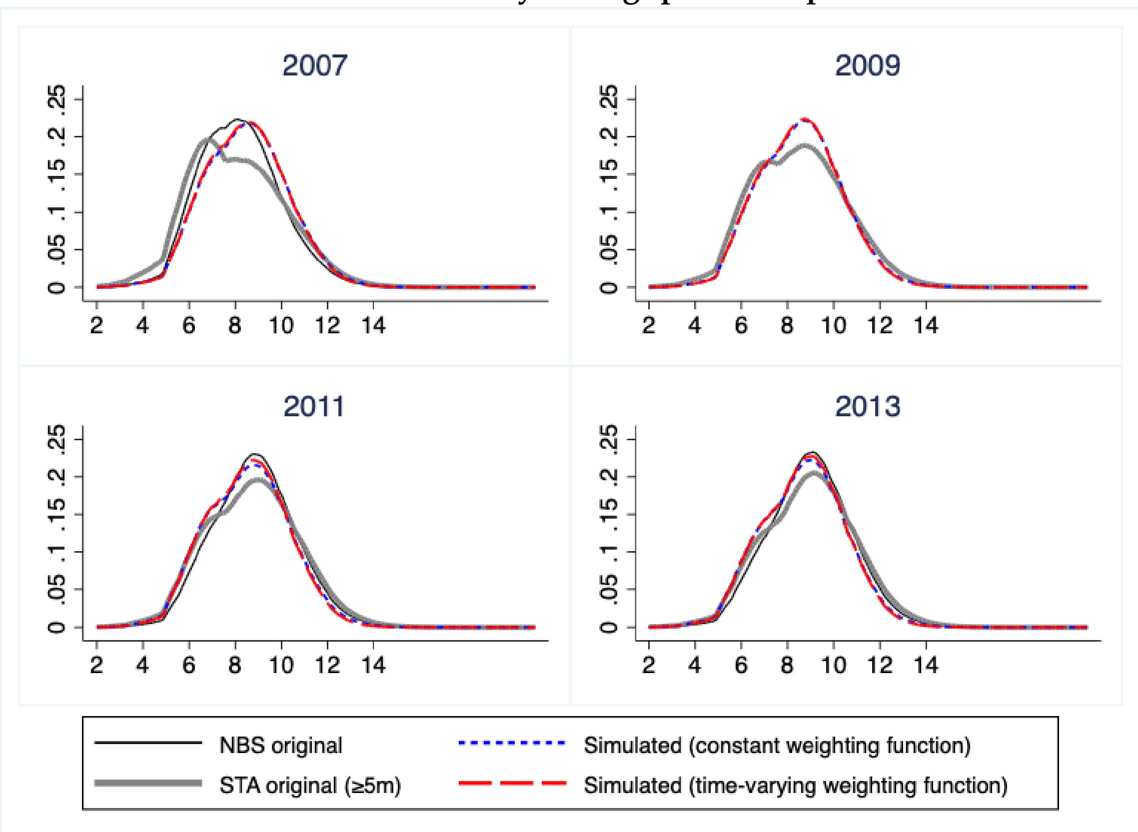


Table 3: Annualized growth rates of output and input variables (2007-2013)

	Value added (nominal)	Gross output (nominal)	Employment (persons)	Fixed asset (purchasing value)	Real capital (constructed)
NBS above-scale survey	–	15.4	11.3	16.2	13.7
STA unweighted	10.4	13.1	1.1	12.2	10.3
Simulated (constant w.f.)	10.4	12.5	5.1	14.6	12.8
Simulated (time-varying w.f.)	9.6	11.5	4.0	13.4	11.5
NBS Yearbook (above-scale)	12.0	15.9	3.6	15.4	

Notes: For the firm-level samples, we first aggregate variables for all manufacturing firms by year and then calculate a single annualized growth rate over the full period. Value added and gross output are in current prices, and real capital values are constructed using a perpetual inventory method (see Brandt, Van Biesebroeck, and Zhang (2014)). For the NBS Yearbook, we report the geometric mean of the reported annual growth statistics. They are for the entire industrial sector, including mining and utilities. The capital statistic is the growth in reported fixed asset at the original purchasing value. The NBS Yearbook reports a growth in industrial GDP for all firms, not limited to above-scale firms, of 11.5%.

data, which changes considerably over time due to the increase in the minimum size threshold and over-reporting of output, the output density in the simulated samples is fairly stable. It only shifts gradually to the right over time, as expected. Second, while the original STA sample over-weights large corporations and focus firms, contains many more small firms in 2007, and is more dispersed, the simulated samples match well with the NBS densities for paid-in capital across the entire time period. Note that we are able to match the very distinct patterns and evolution of the densities of both variables using only a single set of weights to sample firms from the full STA sample.

The densities constructed using the simulated samples based on the constant weighting function (in blue) and the time-varying weighting function (in red) are relatively similar. For the left tail, this is by construction as the change in the NBS reporting threshold makes it impossible to estimate the importance of small firms after 2010, and requires us to use 2007 weights in all later years. In the right tail, the two series depart more in 2011 and 2013 than in 2009. Although differences are not huge, they are not negligible in comparison with the limited extent to which either line departs from the unweighted STA distribution (in gray).

In Table 3, we report the growth rates of value added, gross output, employment and real capital for the period 2007-2013 for the same four samples. We also show the growth rates based on aggregates for the same sector as reported in the Statistical Yearbook (also limited to above-scale firms). Consistent with the earlier discussion, the NBS above-scale survey shows much higher growth rates for gross output, employment and fixed capital compared to the original STA survey. For example, nominal gross output increased at an annual rate of 15.4% in the NBS sample, but 13.1% in the STA data; in the case of capital the two growth rates are 13.7% versus 10.3%. Applying either weighting scheme to samples from the STA survey reduces the growth rate of gross output, while raising the growth rates for employment and capital. Growth rates for employment for the simulated samples are slightly higher than those for the summary data in the Statistical Yearbook, but growth rates for gross output and value added are 4 and 2 percent lower, respectively. These differences are expected to lower productivity growth estimates for the simulated samples.

Based on the simulated sample, the two panels in Figure 4 show the changing composition of key variables by ownership and region. Most prominent is the rapidly rising share of the non-state sector, which occurs largely at the expense of the state sector. By 2013, non-state firms account for nearly sixty percent of output and employment in manufacturing. The role of foreign firms grows significantly between 1998-2007, but then begins to retreat for every variable. In contrast, changes in the regional composition of industrial activity are negligible, as shown in Panel (b).

4. Production function estimation

To calculate firm-level productivity, we need to estimate the production function. We use the two-stage approach of Gandhi, Navarro, and Rivers (2020) (GNR), which has a number of advantages over alternative methodologies. First, it assumes a non-parametric production function which provides a flexible characterization of technology. Chen et al. (2021a) use the same methodology to allow for flexible technology differences between private and publicly-owned firms. Second, the use of information on the first order condition for material input helps to estimate the material inputs' output elasticity. Papers estimating productivity with the control function approach of Ackerberg, Caves, and Frazer (2015) often find very high material elasticity for China. And third, it has the advantage over the index number method used in Brandt, Van Biesebroeck, and Zhang (2012) of estimating returns to scale freely.

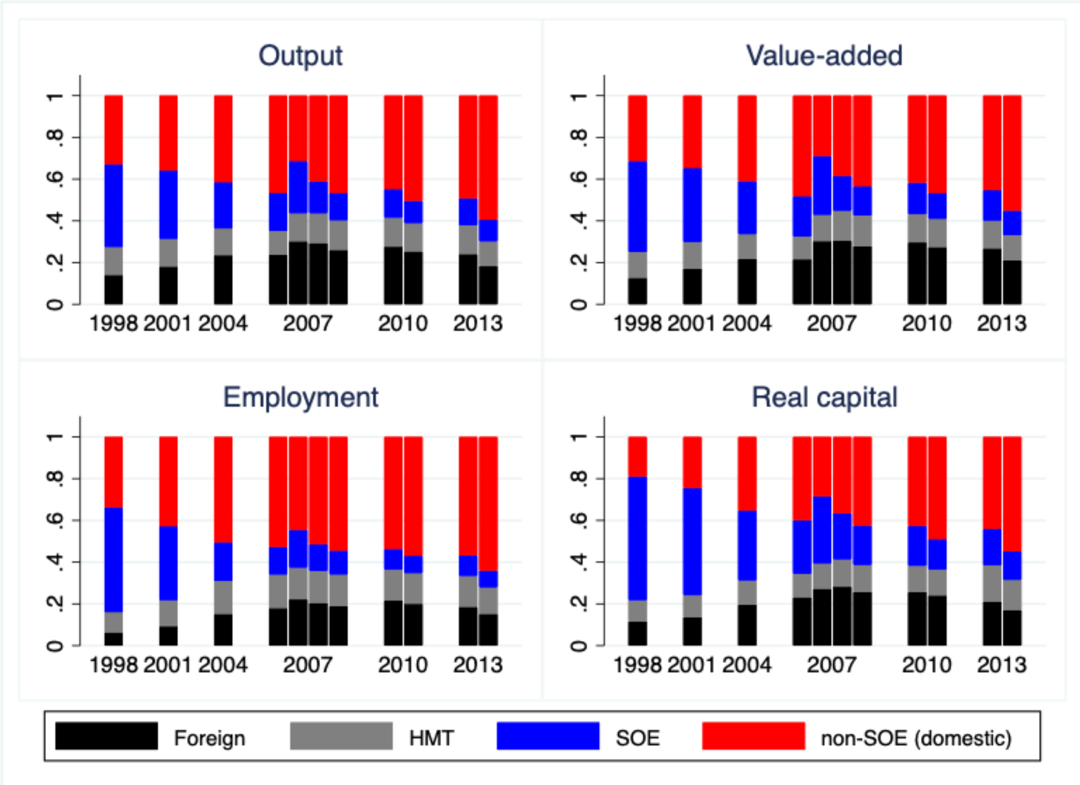
The production technology is specified as:

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + \omega_{it} + \varepsilon_{it} \qquad \text{with } \omega_{it} = \rho\omega_{it-1} + \eta_{it}. \tag{7}$$

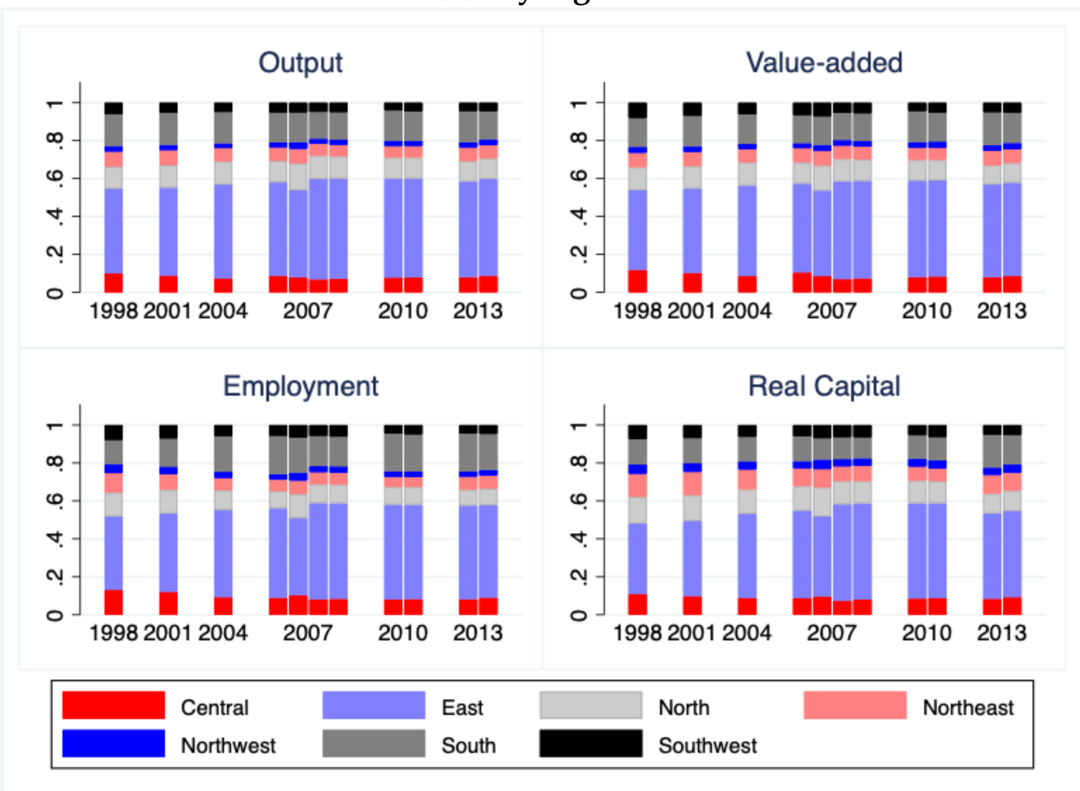
The deterministic part is a non-parametric input-aggregator $f(\cdot)$, firm-level productivity ω_{it} is assumed to follow an AR(1) process with innovation η_{it}, and ε_{it} is the idiosyncratic error assumed to be unobservable to firms when they make their input choices. The first estimation stage identifies its derivative with respect to material use from the first-order condition for materials. The method then integrates that derivative back to the production function. To facilitate that integration, the production function is approximated by a polynomial in inputs. The non-parametric production function leads to output elasticities that are firm-specific as different firms

Figure 4: Evolution of the sample composition

(a) By ownership type

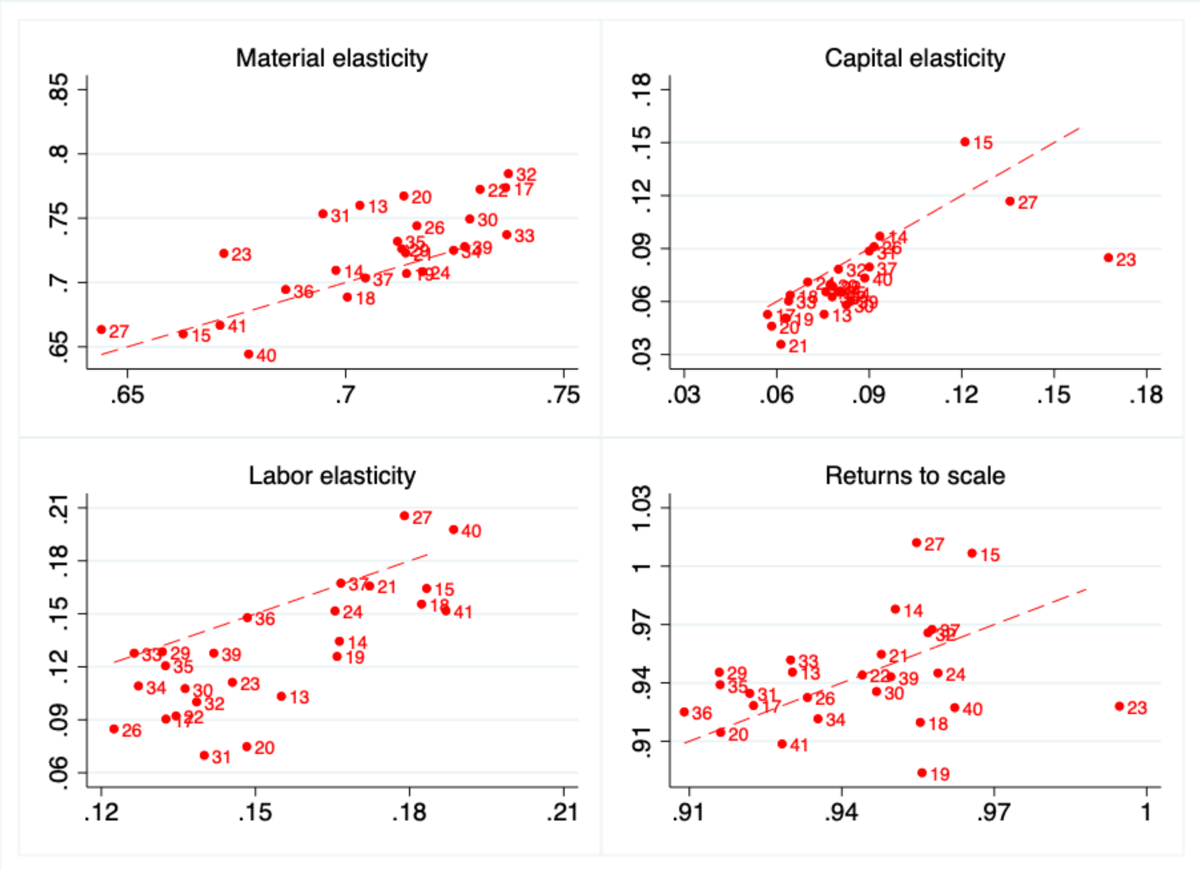


(b) By region



Notes: The single bars in 1998, 2001, and 2004 are for the NBS sample. The four bars in 2007, from left to right, correspond to the NBS sample, the unadjusted STA sample, the simulated sample with the constant weighting function, and the simulated samples with the time-varying weighting scheme. The two bars in 2010 and 2013 are based on the two simulated samples, constant weighting function on the left and time-varying weighting function on the right.

Figure 5: Output elasticities estimated on 1998-2007 and 2007-2013



Notes: The first three panels show the output elasticities for the three inputs estimated using a non-parametric production function. The horizontal axis shows the estimates for 1998-2007 on the NBS data and the vertical axis the estimates for 2007-2013 on the samples simulated with a time-varying weighting function. The fourth panel shows returns to scale calculated as the sum of the three elasticities. All values are the median across all firms in a 2-digit CIC industry (codes indicated next to the markers). The dashed line is the 45-degree line. Comparable results for samples based on a constant weighting function are in Figure B.1 in the Appendix.

operate at different points.

We estimate the production function separately for the periods before and after 2007, allowing the importance of inputs as well as the substitution between them to change flexibly over time. We use the original NBS survey on the 1998-2007 period and the simulated samples from the STA survey on the 2007-2013 period.[17] In Figure 5, we compare for each 2-digit industry the median values of output elasticities and returns to scale estimates for the two periods. The position relative to the (dashed) 45-degree line indicates that material elasticities increased over time in all industries; capital elasticities changed the least, and labor elasticities fell in most industries. Returns to scale, plotted in the lower-right panel, are slightly higher in the later period and are close to one in almost every industry after 2007.

[17] The benchmark estimates are based on the simulated samples obtained using the time-varying function. Results based on the constant weighting function samples are very similar. If not reported in the main tables and figures, they are either in the Appendix or available from the authors upon request.

There are a number of explanations for the higher material elasticity after 2007. First, it may reflect changes in technology. In a more developed economy, we expect greater specialization and less vertical integration, such that firms outsource more intermediate inputs. Second, since the output elasticity for intermediate inputs is identified from its revenue share, over-reporting of intermediate inputs and/or under-reporting of revenue may introduce an upward bias in the elasticity estimate. In Section 5.3, we examine the robustness of the TFP growth estimates to such potential estimation bias.

5. Results

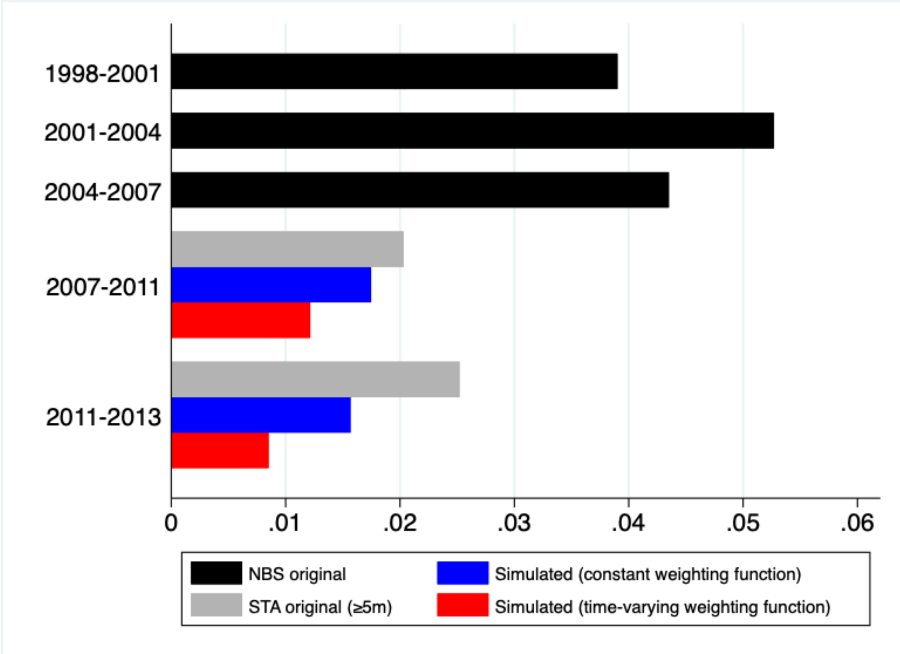
We calculate firm-level productivity $\widehat{\omega}_{it}$ as a residual from the production function (7) and aggregate to the industry-level productivity $\widehat{\Omega}_t = \sum_i s_{it}\widehat{\omega}_{it}$, using output shares as weights. Annualized productivity growth for the entire Chinese manufacturing sector, shown in Figure 6, is then the output-weighted average of industry-level productivity growth rates. Growth rates are calculated over several intervals that span the entire 1998-2013 period. The first three statistics (shown in black) are calculated on the NBS sample for three 3-year intervals in 1998-2007. These estimates are slightly higher than the 3.4 percent annual growth rate reported in Brandt, Van Biesebroeck, and Zhang (2012) over the same period.[18] One reason for this is that the GNR method estimates diminishing returns to scale in all industries. In contrast, the index number methodology used by Brandt, Van Biesebroeck, and Zhang (2012) assumes constant returns to scale. At a time of rapidly rising input use, especially materials and capital, this leads to lower productivity growth estimates.

For the later periods, 2007-2011 and 2011-2013, three sets of results are shown.[19] The results in light gray use the original STA sample, limited to firms with annual output above 5 million RMB. The other two results are the averages over 5 simulated, representative samples obtained using either constant or time-varying weighting functions. Estimates using either weighting function imply a significant slowdown after 2007, with productivity growth between 2007-2013 approximately only one third of the growth rate between 1998-2007. Both set of estimates are also lower than those obtained using the original STA data directly, highlighting the importance of the weighting.

[18]Productivity growth in Brandt, Van Biesebroeck, and Zhang (2012) using their preferred estimate for a gross output production function is 2.9 percent per year. It involves a number of adjustments for unmeasured human capital increases and unreported labor income that lowered the annual growth rate from 3.4 percent.

[19]We use 2007-2011 and 2011-2013 rather than 2007-2010 and 2010-2013 because 2010 NBS micro data are not available. The estimates on the simulated STA samples with time-varying weights cannot be calculated in that year.

Figure 6: Annualized aggregate productivity growth in China's manufacturing



Results for year-on-year growth rates are reported in Figure B.2 in the Appendix. These estimates show broadly the same pattern, but exhibit more volatility, especially after 2007. For example, productivity growth declines sharply between 2008 and 2009 during the Great Recession, followed by an even stronger, stimulus-fueled recovery.[20] For the last few years for which we have estimates, productivity growth is again much lower.

5.1 Heterogeneity

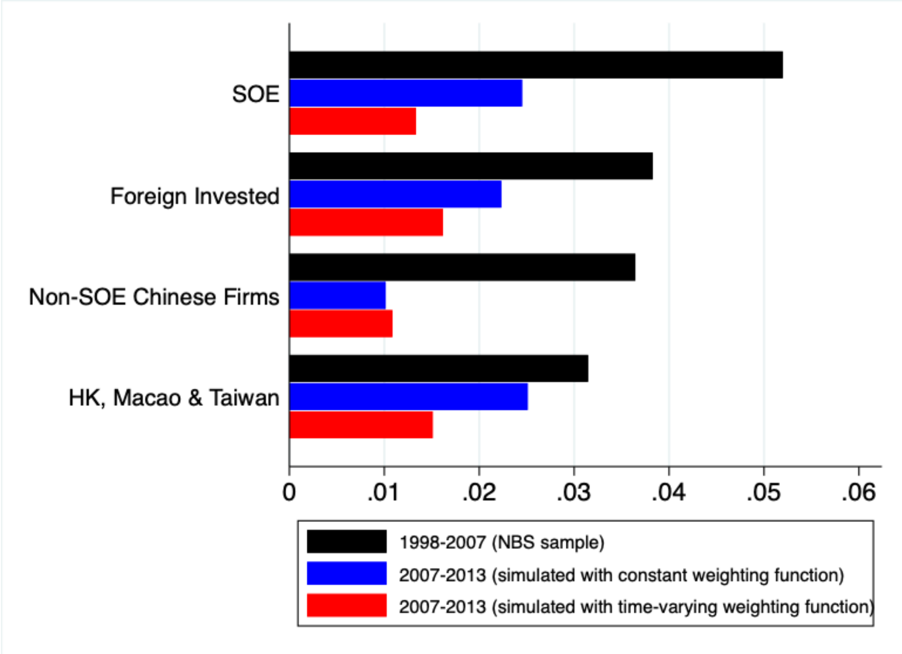
We examine differences in productivity growth by ownership, industry and region.

5.1.1 Ownership

Figure 7 shows productivity growth rates for firms of different ownership types for the two periods. Between 1998-2007, all ownership categories show robust productivity growth of at least 3 percent per annum, but state-owned enterprises (SOEs) performed especially strong. This reflects two key forces. First, many SOEs cut a significant share of their workforce to eliminate redundant workers (Hsieh and Song, 2015). Second, the state retreated from more labor-intensive industries where it

[20] Changes in aggregate productivity growth are less extreme in both directions for the weighted, simulated samples. Recall that both series use the 2007 pre-crisis weights for small firms which likely overestimates their importance during the recession years as small firms tend to suffer most (less entry and more exit). Whether this biases the aggregate productivity growth estimates depends on whether small firms' productivity growth evolution is better or worse than that of larger firms (something we cannot assess with the non-representative tax sample) and on where in the firm productivity distribution small firms enter (which we discuss below in Section 5.2).

Figure 7: Productivity growth by ownership type



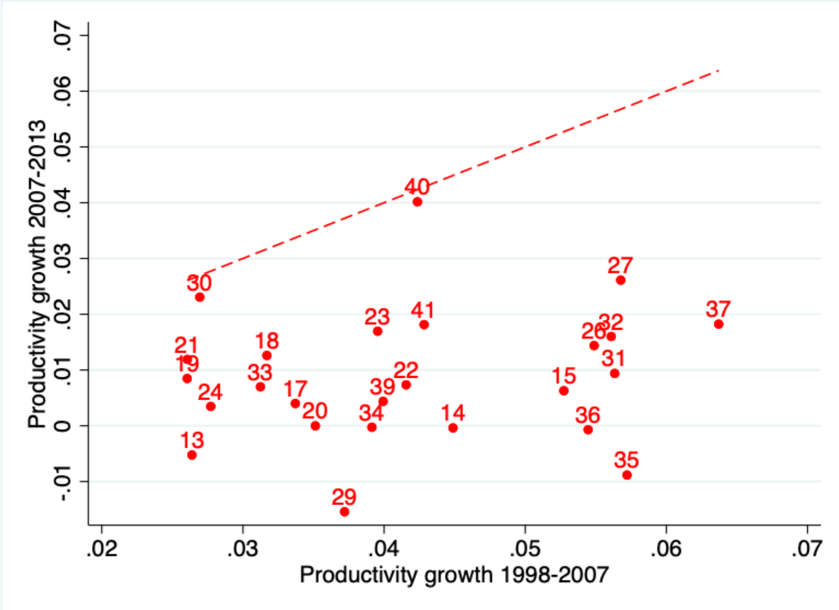
has no comparative advantage. As a result, many small and inefficient SOEs were either privatized or allowed to go bankrupt, which contributed to the decline in SOE's share of value added from 42% to 20%. Eliminating the lower tail of the TFP distribution contributes to faster TFP growth for the SOE ownership category through a compositional effect.[21] Our finding that SOEs as a group achieved higher TFP growth is consistent with the existing literature—see, for instance, Hsieh and Klenow (2009) and Hsieh and Song (2015).

After 2007, productivity growth declined significantly for firms in every ownership category. SOEs, whose share of manufacturing value added continued to decline, experienced the largest absolute decline in productivity growth. Outside the state sector, private (non-SOE Chinese) firms experienced the largest reduction, with productivity growth less than one third of the pre-2007 growth rate. They experienced the lowest productivity growth of all ownership types, averaging only slightly more than one percent. Moreover, this occurred in the context of a significant rise in their share of the outcome variables reported in Figure 4. One possibility for slower TFP growth for private firms is their stronger incentive to under-report output or over-report inputs for tax evasion purposes. Estimates of productivity growth based on the two weighting schemes are fairly similar for each ownership type, but more sensitive to the weighting scheme in the case of SOEs and firms from Hong Kong, Macao and Taiwan.

In the context of the debate over the advance of the state at the expense of

[21] Note that it does not imply that SOEs have higher TFP levels than private firms as our analysis focuses specifically on TFP growth—not TFP level—generated by all firms in an ownership category.

Figure 8: Productivity growth by industry



Notes: The results for 2007-2013 use samples simulated with the time-varying weighting function. Results based on the constant weighting function are in the Figure B.3 in the Appendix. The exact productivity growth estimates by industry are reported in Table B.1 in the Appendix. The dashed line is the 45-degree line.

the private sector, our estimates reveal that the sharp reduction in the growth of productivity after 2007 is largely a product of behavior in the non-state sector. Resources continued to flow to private firms, contributing to the sector's rising share of employment, capital and output, at the same time that productivity growth faltered. Productivity growth slowed only slightly less for foreign-invested firms, which as a group contracted in relative terms.

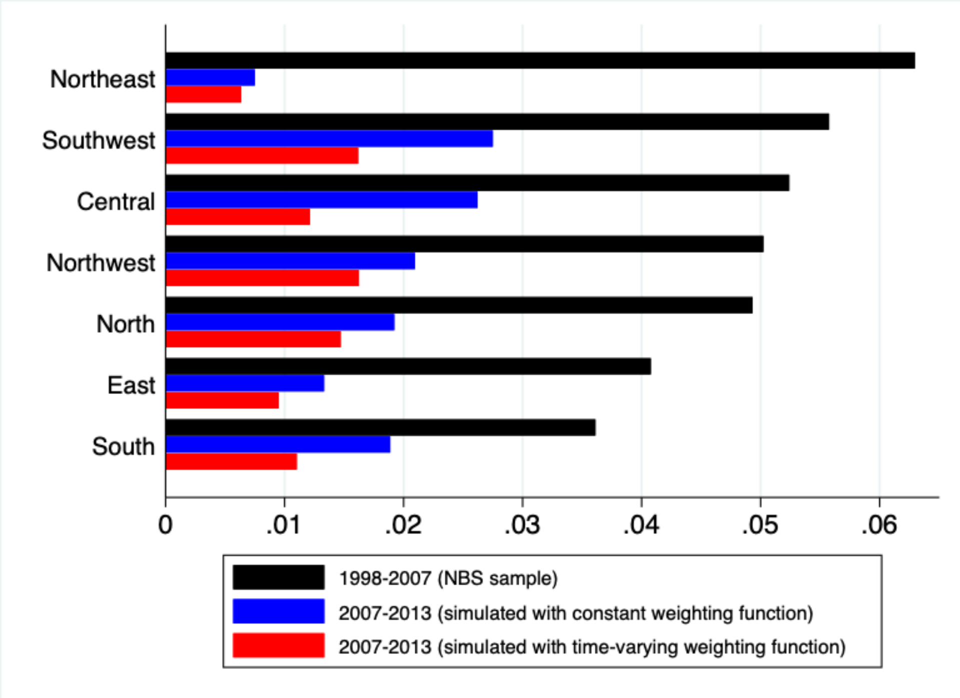
5.1.2 Industry

Figure 8 shows productivity growth rates for the 25 2-digit industries in both periods.[22] Industry-level productivity growth is positively correlated over time with a partial correlation statistic of 0.36. Most notable, growth rates are uniformly and significantly lower in the later period, with all but one industry lying below the 45 degree line. The average productivity growth across all industries declines from 4.4 to 1.4 percent from 1998-2007 to 2007-2013. Communications Equipment and Electronics (CIC 40), which experienced productivity growth in excess of 4 percent per year in both periods, is a clear outlier. Partly due to this outlier, the standard deviation declines only from 0.14 to 0.11.

In a handful of important industries, e.g., Metal Products (CIC 34), General

[22] Because of their small sample sizes, we exclude Tobacco (CIC 16), Oil Processing and Coking (CIC 25), and Chemical Fibre (CIC 28). The STA survey does not cover Weapons and Ammunition (CIC 38). We also exclude the miscellaneous category (CIC 42) from the analysis.

Figure 9: Productivity growth by region



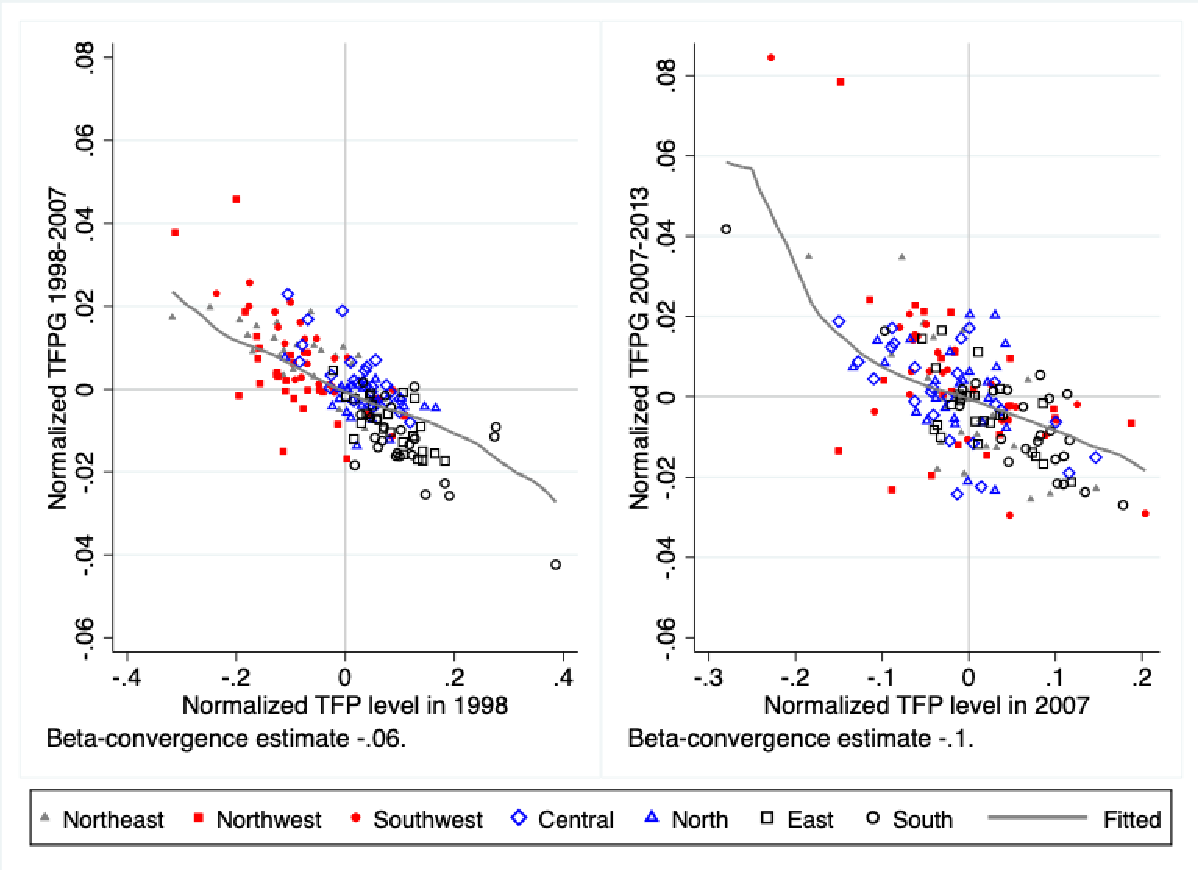
Machinery (CIC 35), and Special Purpose Machinery (CIC 36), productivity growth is close to zero or even negative. In other industries that experienced robust growth between 1998-2007, we see a sharp reduction in productivity growth in absolute terms, e.g., Food Manufacturing (CIC 14), Chemical Products (CIC 26), Rubber and Plastics CIC (29), and Electric Machinery and Equipment (CIC 39). Paradoxically, firms in some of these same industries (CIC 26, 35, 36 and 39) account for a particularly high share of all invention patents by China's manufacturing sector between 2001-2013 (Wu, Lin, and Wu, 2022).

5.1.3 Region

Figure 9 captures stark differences in productivity growth rates across regions. Between 1998-2007, growth was strongest in the Northeast, Southwest and Central China—regions that lagged the rest of the country in GDP growth through the first two decades of reform and benefited most from SOE restructuring—and weakest in the South and the East. But even in these regions, productivity growth exceeded 3.5 percent per annum. After 2007, productivity growth falls sharply everywhere, but it collapsed especially in the Northeast. Productivity growth also slows considerably in the East and South, the source of more than 80% of China's manufacturing exports up to 2007 ((Brandt and Lim, 2024)).

As a result of these patterns, the level of productivity converged across regions. Figure 10 plots TFP growth against initial TFP at the region-industry level for the periods 1998-2007 and 2007-2013. Each point represents an industry by region pair.

Figure 10: Persistent productivity convergence across regions



Notes: Each point represents an industry by region combination. TFP levels and growth rates are both demeaned across all regions within each industry. The graph in the right panel for 2007-2013 is based on simulated samples with the time-varying weighting function.

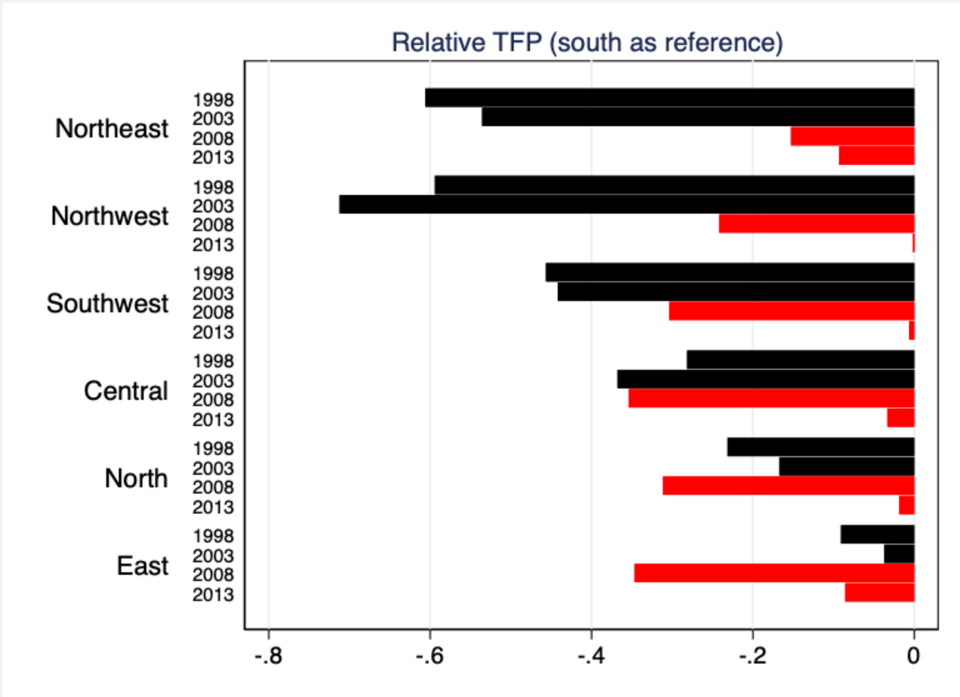
The values for both the productivity levels and growth rates are demeaned across provinces within each industry. The negative slopes of the two regression lines indicate rapid convergence in productivity across regions within industries. The rate of β-convergence is 6 percent between 1998 to 2007, and even strengthened to 10 percent from 2007 to 2013. A β-convergence rate of 7 percent implies that it takes 10 years to halve an initial gap in TFP in levels between two provinces.[23]

Convergence can be an important source of TFP growth, but it is silent about the absolute magnitude of aggregate productivity growth. After 2007, regional differences continued to narrow, however it largely reflected lackluster TFP growth in the high-productivity provinces in the South and East as opposed to economic dynamism in lagging provinces. Recall from Figure 9 that TFP growth between 2007-2013 was only 1 percent per annum in China's most developed regions and only slightly higher elsewhere.

Figure 11 shows the evolution of the gap between each region's TFP level relative to the South, the reference province. Our estimates suggest that there is

[23]Estimates are slightly lower if we instrument the initial TFP level with either lagged values or alternative measures to deal with problems of measurement error and division bias.

Figure 11: Evolution of productivity levels across regions



Notes: The relative TFP level of each region is computed as a weighted average of productivity differences from the South (the reference region) across industries. The weights are two-digit CIC industry gross output shares at the national-level. Estimates for 1998 and 2003 are based on the NBS above-scale sample, while estimates for 2008 and 2013 utilize simulated samples with the time-varying weighting function.

only limited room left for regional convergence as a future source of TFP growth. In most regions, the gap with the South has narrowed significantly over time. By 2013, the average remaining gap is only 5 percent of the South's TFP level.

5.2 The changing role of new entrants

We have documented a sharp decline in the aggregate productivity growth that cuts across industries, ownership, and provinces. It naturally raises the question: What is responsible for this decline? A natural candidate explanation is the changing nature of the market selection mechanism. Brandt, Van Biesebroeck, and Zhang (2012) highlight the important role of net entry as a primary driver of aggregate productivity growth between 1998 and 2007. Brandt, Kambourov, and Storesletten (2025) argue that the downsizing of the state sector in the late 1990s and early 2000s played a critical role in reducing barriers to entry for non-state firms and removing a source of negative selection into the manufacturing sector. As a result, new entrants tended to be more productive than before. Other reforms that reduced the fixed costs of entry may have increased the overall rate of entry, but also lowered the relative productivity level of new entrants. However, coupled with a strong market selection mechanism that weeded out the weakest firms and rapid productivity growth for surviving firms, entry was an important source of dynamism.

Unfortunately, the original decomposition cannot be replicated for 2007-2013. The source data no longer cover the universe of above-scale firms, as in the NBS survey. The STA survey is not designed to include all firms or be representative of the entire economy. Firms that enter or exit the STA sample do not necessarily enter or exit from the economy, but largely reflect the sample rotation scheme. Moreover, our weighted sampling scheme is intended to simulate a representative sample for each year, not follow individual firms over time.

Even though we can no longer identify true entry or exit, we do observe firms' age, which allows us to distinguish between incumbents that have been in operation for some time and younger firms that entered more recently. These definitions of incumbents and recent entrants are unrelated to the number of years we observe firms in the STA sample. Aggregate productivity growth is defined as the change in the size-weighted average firm-level productivity and we can perform that calculation separately on the subsets of incumbents and young firms. A comparison of the end-period productivity level for each of the two groups with the initial industry average provides insights into their contribution to industry-level productivity growth.

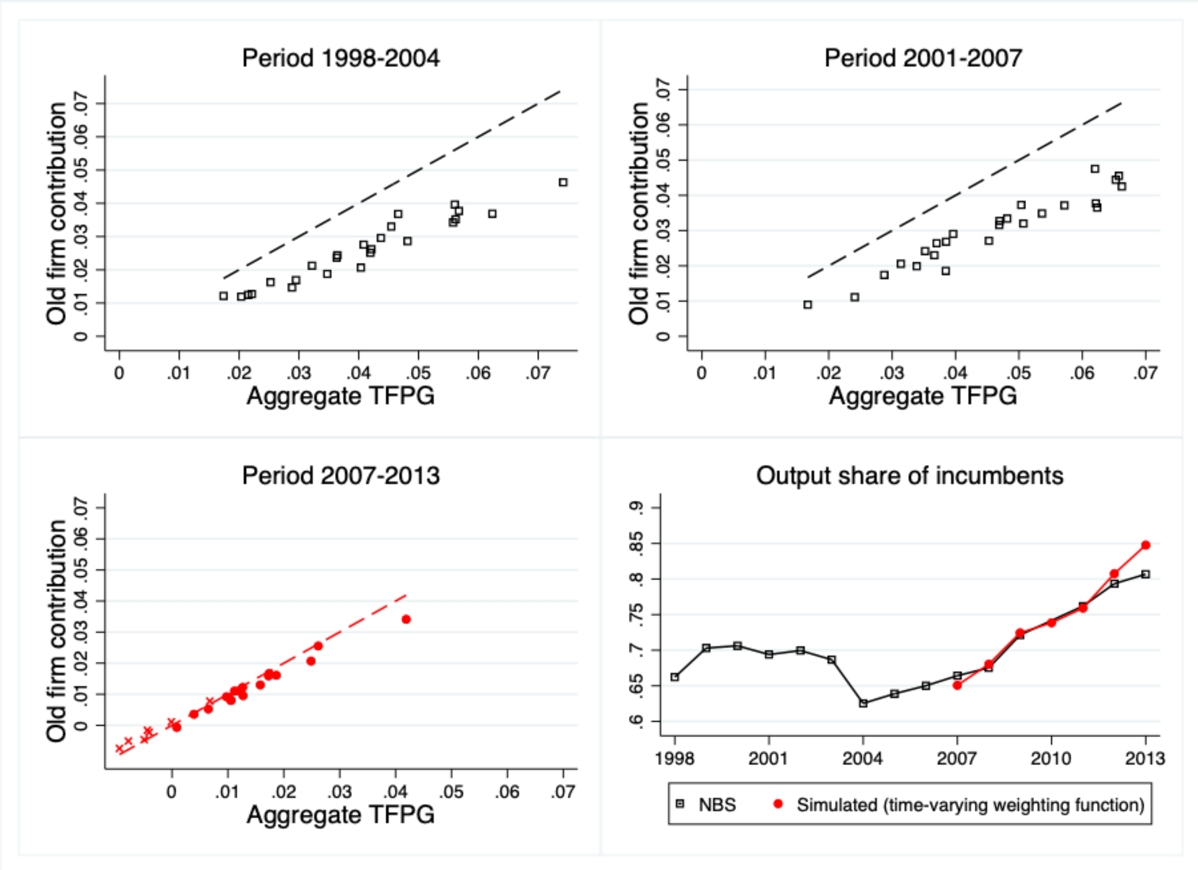
This TFP growth decomposition differs from Brandt, Van Biesebroeck, and Zhang (2012) in several respects. First, we measure productivity on a gross output rather than value-added basis. Second, we solely use firm age to distinguish between continuing and young firms and disregard the timing of a firm's first appearance in the sample. Third, we modify the commonly-used decomposition that relies on firm-level changes. Our alternative approach simply compares the final TFP level of each group of firms to the initial aggregate TFP level. It does not measure the TFP change for each group, but rather the contribution of each group to the final aggregate TFP level.

Our modified decomposition for the change in aggregate TFP from year 0 to year t is

$$\overline{\omega}_t - \overline{\omega}_0 \quad = \sum_{i \in OLD} s_{it} \left(\omega_{it} - \overline{\omega}_0 \right) + \sum_{e \in YNG} s_{et} \left(\omega_{et} - \overline{\omega}_0 \right), \tag{8}$$

where $\overline{\omega}$ is aggregate productivity and s denotes the output weights in the actual and simulated samples. The productivity measures are in logarithms, such that both terms represent an aggregate percentage change, and we express them in annual changes. The second term measures the contribution of entrants. Except for the different definition of entrants, i.e., young firms rather than newly appearing firms, it is the same as in the standard decompositions. The first term captures all other effects. This includes both the contribution of continuing firms, i.e., firm-level productivity changes and between-firm changes in output shares that affect aggregate

Figure 12: Contribution to aggregate productivity growth of old firms (> 6 years)



Notes: The results for 2007-2013 use samples simulated with the time-varying weighting function. X markers represent 2-digit industries where young firms contribute negatively to industry-level productivity growth. From left to right, these are CIC29 (rubber products), CIC35 (general machinery), CIC13 (food processing), CIC36(special equipment), CIC34 (metal products), CIC14 (food manufacturing) and CIC39 (electrical machinary).

productivity, as well as any aggregate productivity change due to firm exit. If the average firm that exits by year t was below the industry average in year 0, it will make a positive contribution in the first term.

In the first three panels of Figure 12, we plot on the horizontal axis the aggregate annual productivity growth rate, $\overline{\omega}_t - \overline{\omega}_0$, and on the vertical axis the contribution of incumbent (old) firms, i.e., the first term of equation (8). Because the fraction of aggregate growth that entrants account for tends to increase mechanically with the length of the period considered, we show results for three partially overlapping periods of exactly 6 years. The lower-right panel shows the evolution of the gross output share of incumbent firms, pooling all manufacturing industries.

Over the three 6-year periods, annualized TFP growth of the manufacturing sector is 3.9%, 4.1% and 1.1%. The TFP level of old firms (incumbents) grows by, respectively, 4.7%, 4.7% and 1.1% per annum from their initial aggregate level. These are computed as the first term on the right hand side of equation (8) adjusted by the total weights of old firms, i.e, $\left(\sum_{i\in OLD} s_{it} (\omega_{it} - \overline{\omega}_0)\right) / \left(\sum_{i\in OLD} s_{it}\right)$. A gap between the industry markers and the 45-degree line indicates the role of entrants, i.e., that the productivity growth of old firms does not account for the entire industry-level growth. Plotting the absolute growth rates further reveals that the gap tends to be larger towards the right. Entrants play a more important role in fast-growing industries, especially in the first two periods.

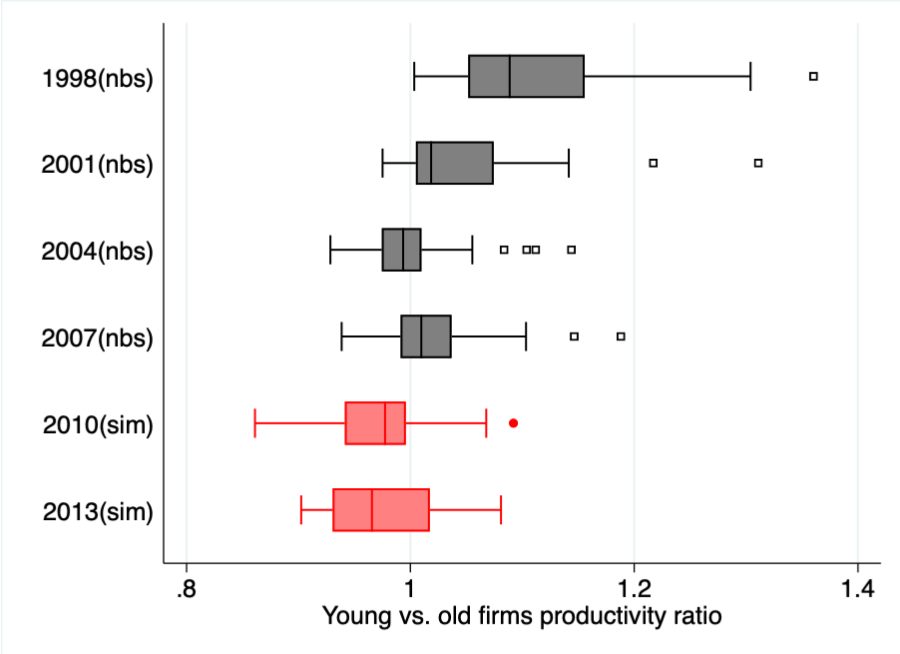
Comparing the top two panels of Figure 12, for 1998-2004 and 2001-2007, with the lower-left panel for 2007-2013, two trends stand out. First, the leftward shift in the markers confirms that productivity growth in all industries is much lower in 2007-2013. Second, the much smaller gap between the markers and the 45-degree line in later periods implies that the contribution of entrants to productivity growth declines over time. The share of aggregate TFP growth that is accounted for by the evolution of incumbent/old firms rises from 69% to 85% and that of entrants', i.e., young firms, declines from 31% to 15%. This combines the impact of changes in the output shares and in the relative productivity levels of the two groups. The smaller relative contribution of entrants coincides with a decline in annual TFP growth from 4.5 percent before 2007 to only 1.1 percent afterwards.

There are a number of industries for which the markers for 2007-2013 period even lie above the 45-degree line.[24] In these industries, the weighted sum of productivity growth of incumbent firms exceeds aggregate growth, implying that the net contribution of young firms to productivity growth is negative. It is a general finding in a Harberger sunrise diagram (Harberger 1998) that a sizable fraction of the poorest-performing firms have a negative contribution. But in a few Chinese manufacturing industries, we find that the entire group of firms of less than six years old is a drag on aggregate productivity growth. This is only possible if the output share of incumbents is sufficiently high. The last panel of Figure 12 reveals the significant increase in the share of manufacturing output that these firms account for. At the height of the post-WTO accession entry boom in 2004, incumbents accounted for a low of 62 percent of output, but this share rose to more than 80 percent in 2013 in the NBS sample. In the simulated samples based on the STA survey, where the reported output estimates are more reliable, their share in 2013 is almost as high as 85 percent.

The much lower contribution of young firms to aggregate productivity growth is the result of two forces: lower TFP levels of new entrants relative to incumbents, and a lower rate of new firm entry. The two may even be linked. In Figure 13 we investigate the first force and show the distribution of the relative TFP levels of new entrants for several years (normalized by industry). New firms are again defined as

[24] These industries are represented by "X" in Figure 12 and listed in the Notes.

Figure 13: Declining relative productivity of young firms (≤ 6 years old)



Notes: The box plot summarizes the distribution of relative productivity of young firms versus incumbents across 2-digit industries. The shaded box represents the inter-quartile range, and the vertical line in the box the median. The simulated samples are based on the time-varying weighting function. The change after 2010 is sharper if we define young firms as no more than 3 years old, as shown Figure B.4 in the Appendix.

firms established within the last six years.[25] Particularly in 1998, but also in 2001 and 2007, the average new entrant had higher productivity than the average incumbent in most industries. In contrast, in both 2010 and 2013, new entrants had productivity levels below incumbents in their first few years in operation in all but a few industries.

The growing importance of private firms in Chinese manufacturing makes it likely that the falling relative productivity of new entrants is driven by the evolution for private entrants. That is indeed borne out in Figure B.5 in the Appendix which shows the evolution separately for the four ownership categories. The relative productivity of new foreign-invested firms and those from Hongkong/Macao/Taiwan declines between 1998 and 2004, and then remains fairly stable. For new SOEs, initial productivity actually increases slightly in the last three data points. In contrast, relative initial productivity of private entrants falls after 2007, and the reduction compared to the 1998 situation is especially pronounced.

Table 4 investigates the second force, showing complementary information on the size of the cohort of new entrants, broken down by firm ownership type. Given the more exhaustive coverage of the NBS survey, new entrants are firms established within the last two years. Consistent with the new NBS size threshold from 2011 onward, we focus throughout on firms with reported revenue above 20 million RMB

[25]Figure B.4 in the Appendix contains a similar figure for new firms established within the last three years.

Table 4: Falling entry rates in the NBS survey

Year	Total	Entry Rate(%)	Share of New Entrants (%)			
			non-SOE	SOE	HMT	Foreign
1998	48,815	7.4	52.9	17.0	14.0	16.2
1999	50,486	6.7	57.5	16.8	13.0	12.8
2000	54,613	5.8	61.6	13.1	12.6	12.8
2001	59,261	7.8	67.0	10.9	11.6	10.5
2002	67,256	7.1	69.0	8.1	11.9	11.1
2003	81,137	7.6	69.0	6.3	12.3	12.4
2004	107,327	11.9	69.1	4.3	12.1	14.5
2005	125,391	8.9	72.3	4.4	10.5	12.9
2006	150,006	8.2	73.0	3.6	10.0	13.3
2007	183,341	8.0	76.3	3.0	9.3	11.4
2008	215,976	8.1	81.1	3.5	7.0	8.5
2009	224,041	5.6	86.7	3.3	5.0	5.0
2011	275,365	5.8	90.8	2.7	3.4	3.1
2012	283,841	5.2	89.7	2.5	4.3	3.6
2013	315,762	4.8	91.7	1.9	3.6	2.8

Notes: Number of firms with reported revenue above 20 million RMB in the NBS annual firm survey. Entrants are firms new to the sample that were established at most one year earlier. The entry rate is the number of entrants divided by the number of active firms at the beginning of the year multiplied by 100.

and firms that are new to the NBS sample. From 2007 to 2013, the share of entrants declined substantially, from 8% of active firms to less than 5%.

The decline is especially pronounced for foreign-invested firms. By 2013, the two types of foreign-invested firms combined represent only 7% of new firms, less than one-third of their share in the mid-2000s. The sharp reduction in the entry rate of foreign-invested firms is confirmed by data from the Business Registry in Table 5, which is not limited to firms with revenue above 20 million RMB.[26] Entry continued to fall sharply after 2014, with the number of new foreign-invested firms entering only 60 percent of the level between 2008-2014. Moreover, their entry is increasingly concentrated in a few technologically advanced manufacturing industries such as pharmaceuticals (CIC 27), transportation equipments (CIC 37), electrical machinery (CIC 39), and telecommunications (CIC 40).

5.3 Robustness to measurement error

We have argued that combining the NBS data for 1998-2007 with the STA data for 2007-2013 has advantages over using the NBS data for 2007-2013, but neither is perfect. We discuss the robustness of our finding of a universal decline in aggregate

[26]The sole omission from the Business Registry is very small family-run enterprises or 个体户.

Table 5: Falling entry rates for foreign-invested firms in manufacturing

Period	Total	Light	Heavy	Advanced
1992-1999	21,790	11,121	7,164	3,506
2000-2007	19,852	8,631	6,914	4,307
2008-2014	6,062	2,561	1,480	2,021
2015-2018	3,419	1,537	765	1,117

Notes: Average number of new entrants per year as defined by their year of establishment, irrespective of size. Light, heavy and advanced are defined at the CIC 2-digit level, and described in the Appendix. *Source:* Business Registry of China.

TFP growth to two important measurement issues.

First, the discussion in Section 2.2 concluded that reforms by the STA lessened under-reporting of revenue and over-reporting of inputs over time. It implies that our TFP growth estimate in the later period can be taken as an upper bound. However, the problem of over-reporting of output and value added in the NBS may have started before 2007, in which case the TFP growth estimate for the initial period might be biased upward. To evaluate this possibility, we show in Table A.2 in the Appendix the annual totals for output (GVIO), value added, and the value-added ratio (VA/GVIO) for both firm-level samples. In addition, we report the ratio between value added of above-scale firms in the NBS survey and GDP in industry as reported in the National Income Accounts.

Between 1998-2007, total value added of above-scale firms increases as a share of GDP in industry in the National Income Accounts from from 57.2 to 106.1 percent, with much of the increase occurring in the last few years. Some of this reflects the growing weight of firms with output values higher than 5 million RMB in the overall size distribution of firms. Some of it also reflects improved statistical coverage of the above-scale survey. The largest jump in the ratio, from 76.7 to 87.8 percent, occurs in 2004, a census year. In that year, the absolute number of firms covered by the NBS annual survey increased by nearly 40 percent. But some of the increase is likely a product of inflated value added in the NBS above-scale survey. The significantly higher ratio of firm-level value added to output in the NBS data compared to the STA, 26.1 versus 19.6 percent, points in that direction.

The implications of over-reporting of value added for TFP growth depend on the reporting of output. In the NBS sample, the ratio of value added to output changes little over time, averaging 26 percent. At face value, this implies that any over-reporting of value added is proportional to that in output, and thus, intermediate inputs, which is the difference between the two. Given that capital and labor input use are reported more consistently in the NBS sample and not subject to the same biases, TFP growth after 2004 is likely biased upward, especially in industries with a low material input intensity. If the value-added ratio in manufacturing actually

Table 6: TFP growth based on alternative production function estimates (%)

	Period and firm sample used		
	NBS 1998-2007	STA 2007-2013	
Production function parameters:		Constant w.fct.	Time-varying w.fct.
NBS 1998-2007	4.5	1.5	1.5
STA 2007-2013			
- Constant weighting fct.	4.2	1.7	
- Time-varying weighting fct.	4.2		1.1

Notes: The statistics on the diagonal are the baseline estimates where TFP growth for each period is calculated using the production function parameters estimated on the same period. The off-diagonal statistics use production function parameters from a different period than the period over which TFP growth is calculated.

declined over time, as suggested by China's input-output tables, value added has to be inflated even more than GVIO, implying larger upward biases in the TFP estimates using the NBS data after 2004.[27]

A second way that misreporting can influence measured productivity growth is through the estimated output elasticities of the production technology which determine the importance of each input in our growth accounting. In the baseline results, productivity is calculated in both periods, 1998-2007 and 2007-2013, using production function parameters estimated on data from the respective period. To verify the robustness of the TFP estimates to this issue, we also calculate TFP growth for both periods using the identical set of production function parameters. Table 6 reports the alternative estimates of aggregate annual TFP growth and the panels in Figure B.6 in the Appendix contrast industry-level TFP growth rates under the same alternatives. While the industry-level estimates are slightly affected, especially in the case of the estimates for 1998-2007, the effect on aggregate growth is minimal.

6. Conclusions

There are many indications that the values firms report in the widely-used NBS annual firm survey have become subject to greater local political influence. It reduces the quality of the data and makes estimates of productivity based on these data after 2007 less credible. We rely on an alternative firm-level survey collected by China's State Tax Administration where these problems are less pronounced to extend earlier productivity estimates. Using simulated samples from the universe of the tax data, with sampling weights based on the distribution of variables that are reported consistently over time in the NBS data, we can calculate aggregate statistics on a sample of firms that is defined consistently over time. We document a large

[27] Across 8 manufacturing industries, the average "direct input coefficient" in China's input-output table rose from 0.72 in 1997 to 0.77 in 2007 and increased further to 0.79 in 2012.

and broad-based decline in TFP growth since 2007 that cuts across all industries, regions, and ownership. The loss of dynamism in China's private sector and a sharply reduced contribution of firm entry to aggregate productivity growth are especially salient. We observe both fewer new firms entering as well as significantly lower (relative) productivity for younger firms.

There are competing interpretations for the sharp drop-off in productivity growth. One possibility is that China may have eliminated the productivity gap in manufacturing with advanced countries, an important source of productivity gains for a developing country. Although the pace of convergence in industry has been faster than in services, recent research suggests that a sizeable productivity gap still remains between China and advanced countries (Zhu, Zhang, and Peng, 2019, Brandt, Li, and Morrow, 2021). External factors may also be important. Overseas demand for Chinese products slowed with the Global Recession, as did international capital in-flows. Productivity growth and business dynamism also declined in advanced countries (Fernald 2015, Decker et al., 2020, Lashkari and Pearce, 2024). For China, sharply falling productivity growth may reflect demand shocks and lower rates of capacity utilization as well as smaller knowledge spillovers.

One explanation we can likely rule out is that it represents the explicit advance of the state sector after 2007 at the expense of the private sector. Indeed, our estimates reveal that the private sector, which expanded most rapidly, lagged other ownership types in productivity growth. Nonetheless, changes in Chinese openness to FDI, as well as shifts in domestic policy, including a lesser role for competition, may be important. A significant portion of China's 4 trillion RMB stimulus program in 2008 went to infrastructure investment that favored upstream, capital-intensive industries that have been laggards in productivity growth. Naughton, Xiao, and Xu (2023) document important shifts in Chinese industrial and regulatory policy since the mid-2000s. Sorting out the contribution of these forces, as well extending the analysis of Chinese productivity behavior past 2013 should be high on our research agenda.

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Appendices

Appendix A. Data

A.1 Data Coverage

The National Tax Statistical Survey is organized jointly by the Ministry of Finance and the State Taxation Administration. While the NBS data only covers firms that have a legal entity, the STA survey also includes non-legal entities with independent accounting systems.

The NBS data for 2008-2013 covers the same sectors as for 1998-2007: mining, manufacturing, and utilities. In contrast, the STA data covers a much broader range of sectors across the entire, i.e., also including agriculture, construction, and services. Throughout, we only focus on the manufacturing sector. Manufacturing firms account for 43.2 percent and 36.2 percent of all firms surveyed in 2007 and 2013, respectively.

The STA data provide more information about the firms than the NBS data. In particular, the number of variables in the former varies from year to year, but counts around 350 to 450. In addition to basic information identifying firms, their operations, and financial performance, which are also included in the NBS data, the STA dataset additionally reports detailed operation information on the value-added tax, consumption tax, business tax, corporate income tax, tariffs, property tax, land appreciation tax, agricultural land occupation tax, vehicle and vessel tax, deed tax, stamp duty, vehicle purchase tax, tobacco tax, resource tax, environmental protection tax, and other taxes and fees.

A.2 Industry classification

Both the NBS and STA data report the industry a firm belongs to using the Chinese Industry Classification (CIC), a part of the National Standards of the People's Republic of China. Originally introduced in 1984, it has been revised several times. To accommodate the dynamic industrial growth, the government consolidated some declining industries and introduced new codes for emerging industries. Over the sample period between 1998 and 2013, the CIC was revised in 1994, 2002, and 2011. For consistency, we developed a concordance table over these three revisions, combining industries that were subsequently split. In total, our more aggregate classification counts 418 manufacturing industries.

A.3 Price deflators

The output deflators for 2008-2013 are calculated based on the producer price index for two-digit industries. The data source is the China Statistical Yearbook. The producer price index increased in 2008, 2010, 2011, and 2012, but declined in 2009 and 2013.

To calculate real value added, we also need input deflators. We construct them from the output deflators and the 2012 National Input-Output Table, following Brandt et al. (2012, 2014). As a robustness check, we calculate an alternative input deflator series using the 2007 Input-Output Table, but given that these tables only change slowly over time, the difference is negligible.

A.4 Ownership

The NBS data include a variable indicating the firm ownership type. A narrow definition of state ownership usually defines it as codes 110, 141, 143, and 151. In earlier years, the number of firms thus defined as state-owned lines up reasonably well with the numbers reported in the Statistical Yearbook. However, the gap widens over time, as some other ownership types increasingly also contain firms under state control, most notably shareholding companies (160). In principle, we can supplement the ownership type indicator with information on the breakdown of registered capital by ownership to help identify firms under state control. However, that information is not observed in the STA data. We therefore used a broader definition of SOEs throughout, one that includes shareholding companies, It results in a count for SOEs that is very close to the numbers reported in China's Statistical Yearbooks in later years.

A.5 Real capital stock

We use the perpetual inventory method to calculate the real capital stock in the STA sample from the 'original value of fixed assets', as in Brandt et al. (2012, 2014). This proceeds in three steps. First, we calculate the nominal capital stock in the firm's founding year. Using the 1993 annual enterprise survey and the NBS data from 1998 onward, we calculate the average growth rate of nominal capital at the province-industry (two-digit) level between a firm's founding year and the first year that it appears in the data. Under the assumption that the firm-specific growth rate of nominal capital equals the average for the same province-industry, we can calculate the nominal capital stock in the firm's founding year based on the first observed investment level. Second, using the investment deflator and assuming a depreciation rate of 9 percent, we use the perpetual inventory method to calculate the real capital stock of a firm in its first year in the data. Third, we can roll this process forward to calculate the real capital stock in all subsequent years from the observed investment information after 2007.

A.6 Merging the two samples

The NBS data provide firm names for all years and the STA data for 2007-2011. The firm IDs in both datasets are consistent, after removing the first 6 digits in the STA firm ID, which represent a geographic codes. As a result, we can merge firms in both dataset first using the firm ID and second the firm names. The results of the merge are reported in Table 1 of the main text.

A.7 Additional summary tables

Table A.1: Number of firms by size category

	Simulated samples			NBS samples		
Year	5-20 m.	20-400 m.	>400 m.	5-20 m.	20-400 m.	>400 m.
2007	117,824	180,088	12,777	123,000	171,443	11,768
2008	165,790	212,131	15,755	158,755	201,443	14,395
2009	172,051	214,572	15,289	131,616	208,776	15,125
2010	174,461	227,476	17,203			
2011	209,343	278,597	19,920	2,531	248,269	26,968
2012	218,324	294,364	20,787	2,565	253,656	30,065
2013	223,901	301,986	21,284	2,311	278,795	36,845

Notes: We do not have access to NBS data for 2010. The minimum size threshold in the NBS data was raised from 5 to 20 million RMB in 2011, which explains the steep drop in the number of small firms in the NBS sample after 2010.

Table A.2: GVIO and value added aggregates in the NBS and STA firm-level samples

	GVIO (trillion RMB)				Value added (trillion RMB)				VA/GVIO (%)				VA/GDP Industry
	NBS	STA(1)	STA(2)	STA(3)	NBS	STA(1)	STA(2)	STA(3)	NBS	STA(1)	STA(2)	STA(3)	(%)
1998	5,861				1,508				25.7				57.2
1999	6,288				1,663				26.4				60.2
2000	7,408				1,945				26.3				63.6
2001	8,247				2,181				26.5				64.2
2002	9,725				2,609				26.8				69.8
2003	12,655				3,390				26.8				76.6
2004	17,458				4,562				26.1				87.8
2005	21,660				5,688				26.3				93.7
2006	27,301				7,200				26.4				100.0
2007	35,175	18,601	30,125	28,552	9,331	3,681	6,317	5,904	26.5	19.8	21.0	20.7	106.1
2008	42,453	23,393	37,149	35,274		4,051	7,139	6,737		17.3	19.2	19.1	
2009	44,270	24,539	38,962	36,882		4,686	7,690	7,229		19.1	19.7	19.6	
2010		33,469	49,594	46,364		6,219	9,516	8,787		18.6	19.2	19.0	
2011	71,164	41,397	58,611	52,295		7,158	10,793	9,514		17.3	18.4	18.2	
2012	75,658	41,529	61,567	55,725		6,922	11,223	10,072		16.7	18.2	18.1	
2013	88,376	41,446	63,894	56,965		7,135	11,836	10,541		17.2	18.5	18.5	

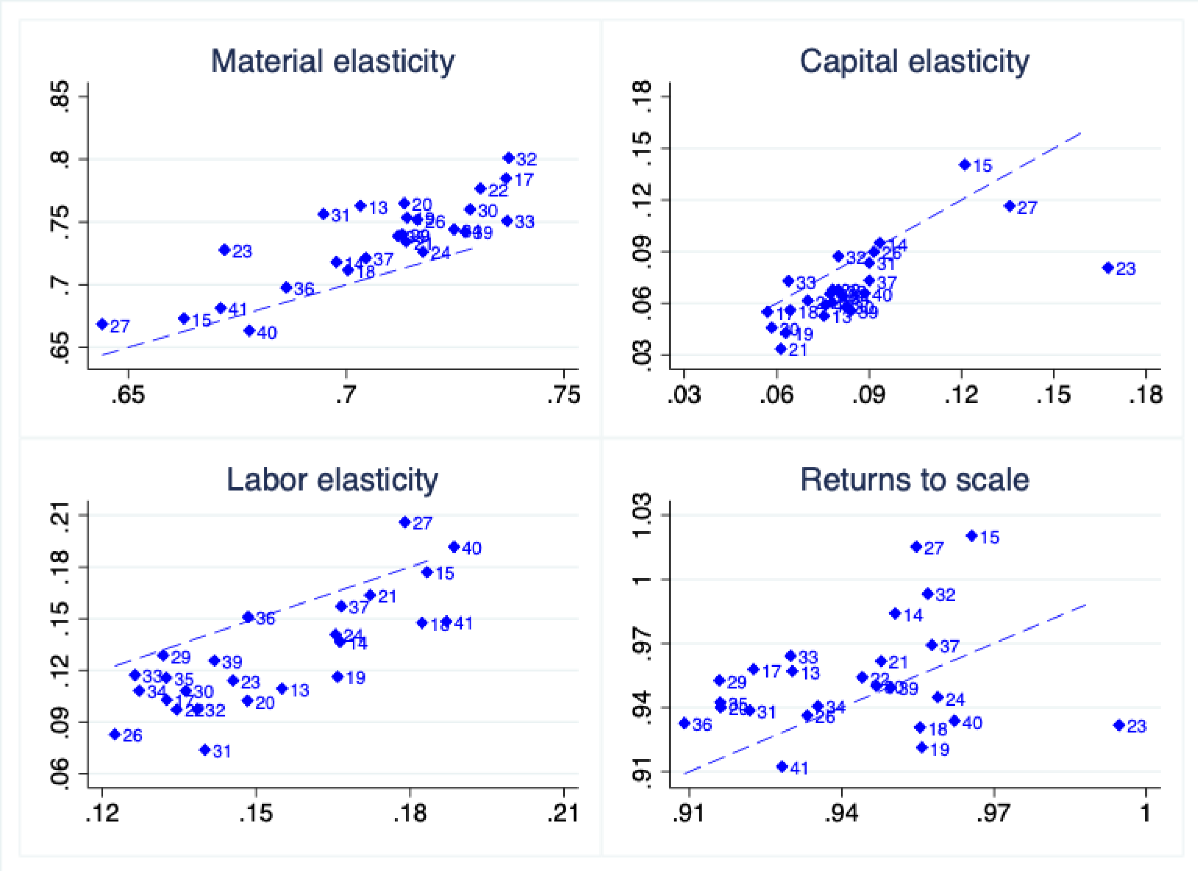
Notes: GVIO is the gross value of industrial output. STA(1) is the unweighted STA sample; STA(2) is the constant-weight STA sample; STA(3) is the time-varying-weight STA sample. VA/GDP Industry is the ratio of value added in industry in the NBS sample to GDP in industry in the national income accounts.

Appendix B. Additional results

Table B.1: Annualized TFP growth rates by industry

CIC description	CIC code	1998-2007	2007-2013 Weighting Function: Constant	2007-2013 Weighting Function: Time-varying
Food processing	13	2.6	-0.7	-0.5
Food manufacturing	14	4.5	0.9	0.0
Beverage manufacturing	15	5.3	1.6	0.6
Textile industry	17	3.4	0.2	0.4
Clothing and other fiber products mfg.	18	3.2	0.8	1.3
Leather, fur, feather and its products	19	2.6	1.3	0.8
Wood/bamboo/rattan/brown/grass prod.	20	3.5	0.4	0.0
Furniture manufacturing	21	2.6	1.0	1.2
Paper and paper products	22	4.2	0.7	0.7
Printing, recording media reproduction	23	4.0	1.6	1.7
Cultural and educational sporting goods	24	2.8	0.8	0.3
Chemical raw materials and chemical prod.	26	5.5	1.2	1.4
Pharmaceutical manufacturing	27	5.7	3.0	2.6
Rubber products	29	3.7	0.1	-1.5
Plastic products	30	2.7	1.5	2.3
Non-metallic mineral products	31	5.6	1.0	0.9
Ferrous metal smelting and rolling proc.	32	5.6	1.6	1.6
Non-ferrous metal smelting and rolling proc.	33	3.1	1.7	0.7
Metal products	34	3.9	-0.1	0.0
General machinery	35	5.7	0.0	-0.9
Special equipment	36	5.4	0.5	-0.1
Transportation equipment	37	6.4	3.6	1.8
Electrical machinery and equipment	39	4.0	1.8	0.4
Electronic and communications equipment	40	4.2	5.3	4.0
Instrumentation & culture, office machinery	41	4.3	2.3	1.8
Total manufacturing		4.5	1.7	1.1

Figure B.1: Output elasticities estimated on two periods (1998-2007 and 2007-2013) (constant weighting function)



Notes: The first three panels show the output elasticities for the three inputs estimated using a non-parametric production function. The horizontal axis shows the estimates for 1998-2007 on the NBS data and the vertical axis the estimates for 2007-2013 on the samples simulated with a constant weighting function. The fourth panel shows returns to scale calculated as the sum of the three elasticities. All values are the median across all firms in a 2-digit CIC industry (codes indicated next to the markers). The dashed line is the 45-degree line.

Figure B.2: Aggregate year-on-year productivity growth in China's manufacturing sector

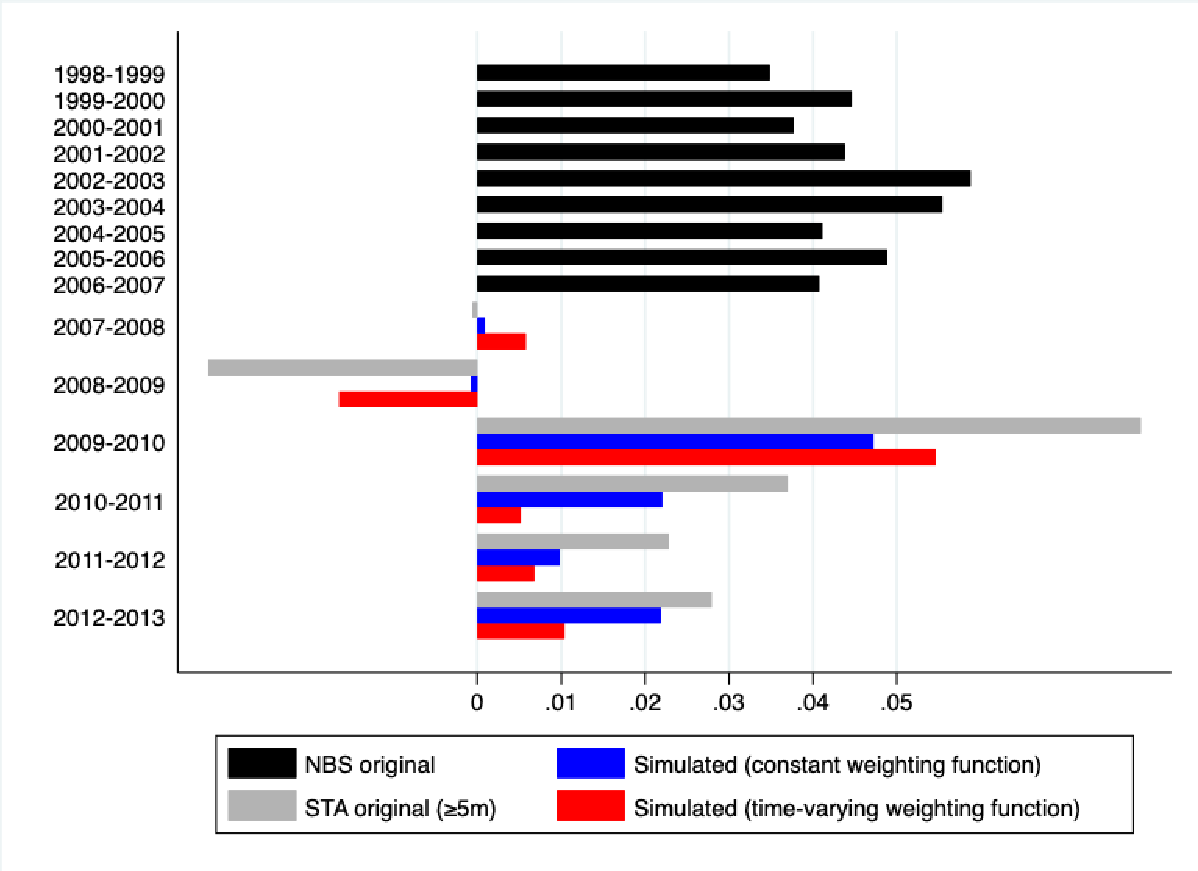
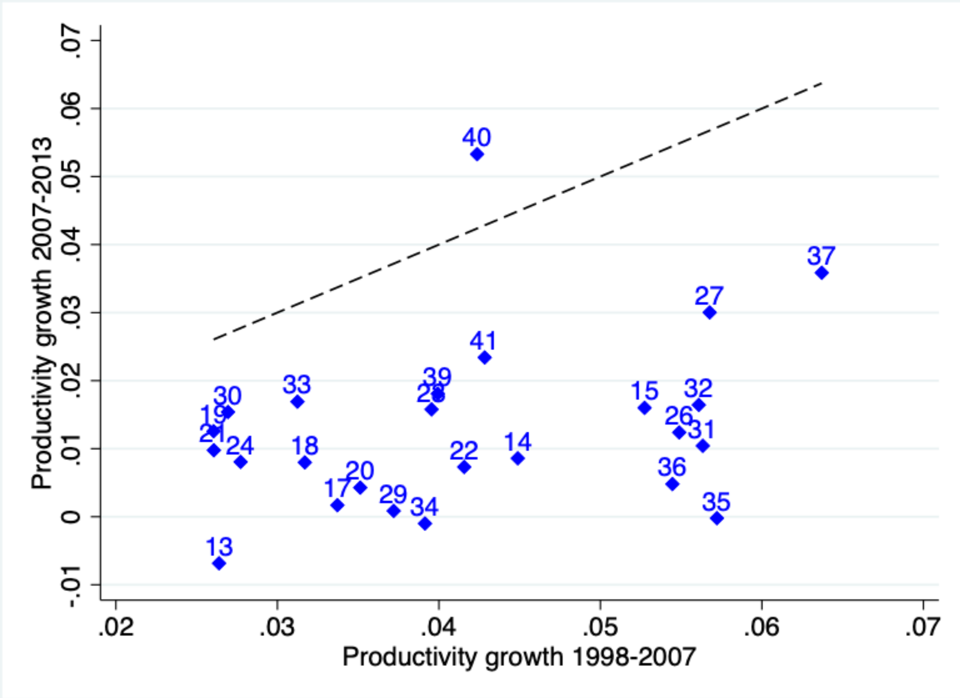
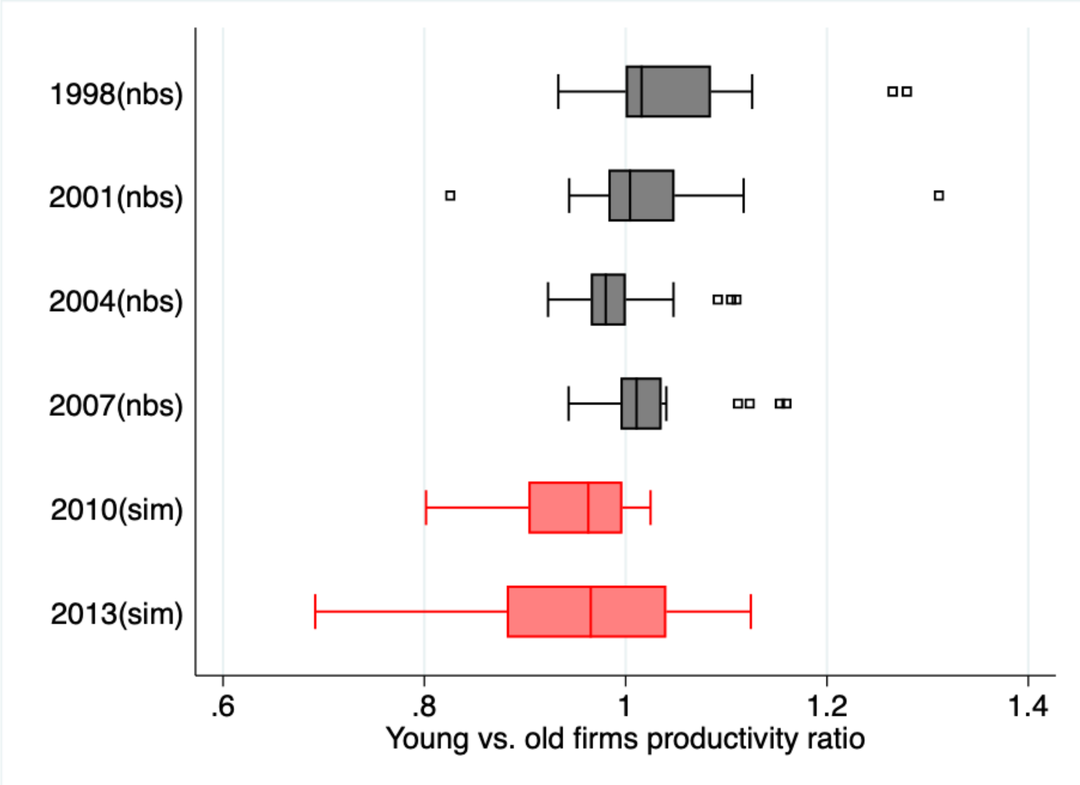


Figure B.3: Productivity growth by industry (constant weighting function)



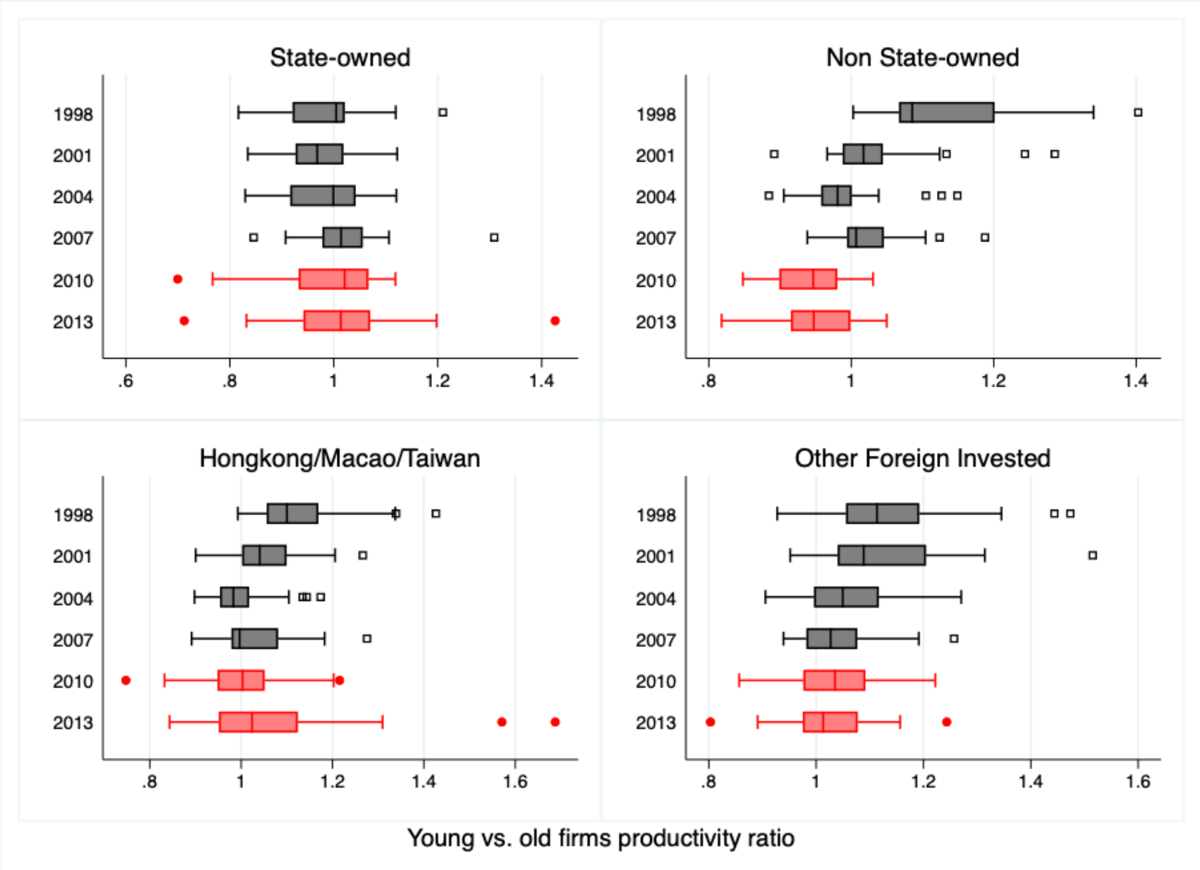
Notes: The results for 2007-2013 use samples simulated with the constant weighting function. The dashed line is the 45-degree line.

Figure B.4: Declining relative productivity of young firms (≤ 3 years old)



Notes: The box plot summarizes the distribution of relative productivity of young firms versus incumbents across 2-digit industries. The shaded box represents the inter-quartile range, and the vertical line in the box the median. The simulated samples are based on the time-varying weighting function.

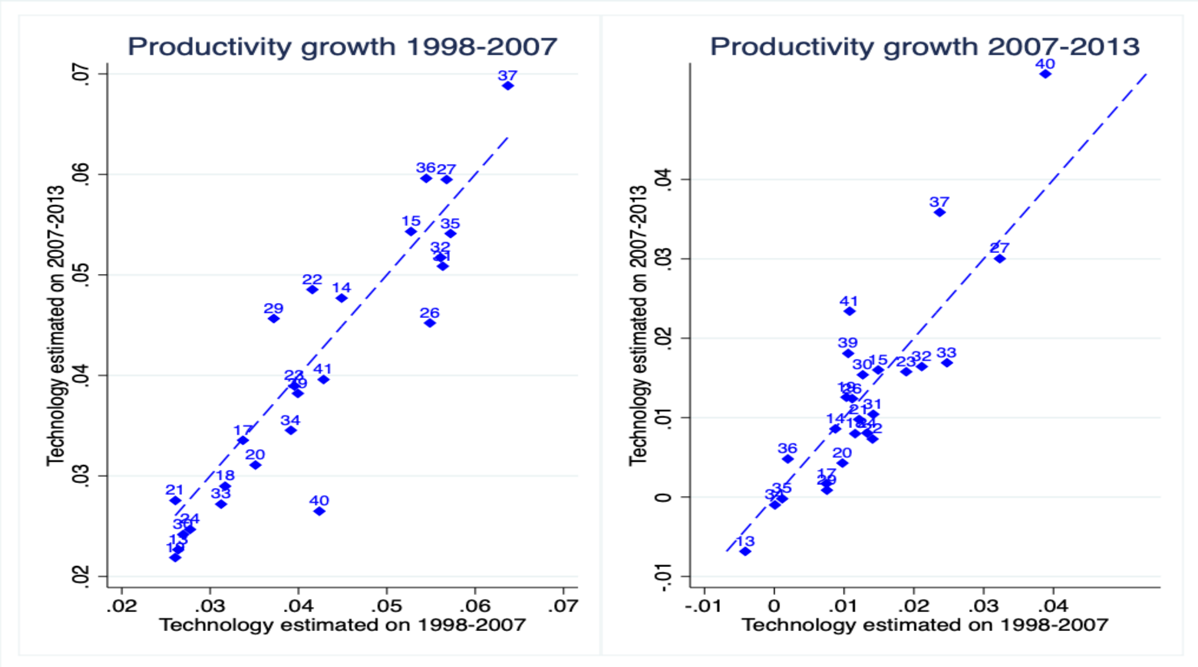
Figure B.5: Declining relative productivity of young firms by ownership (≤ 6 years old)



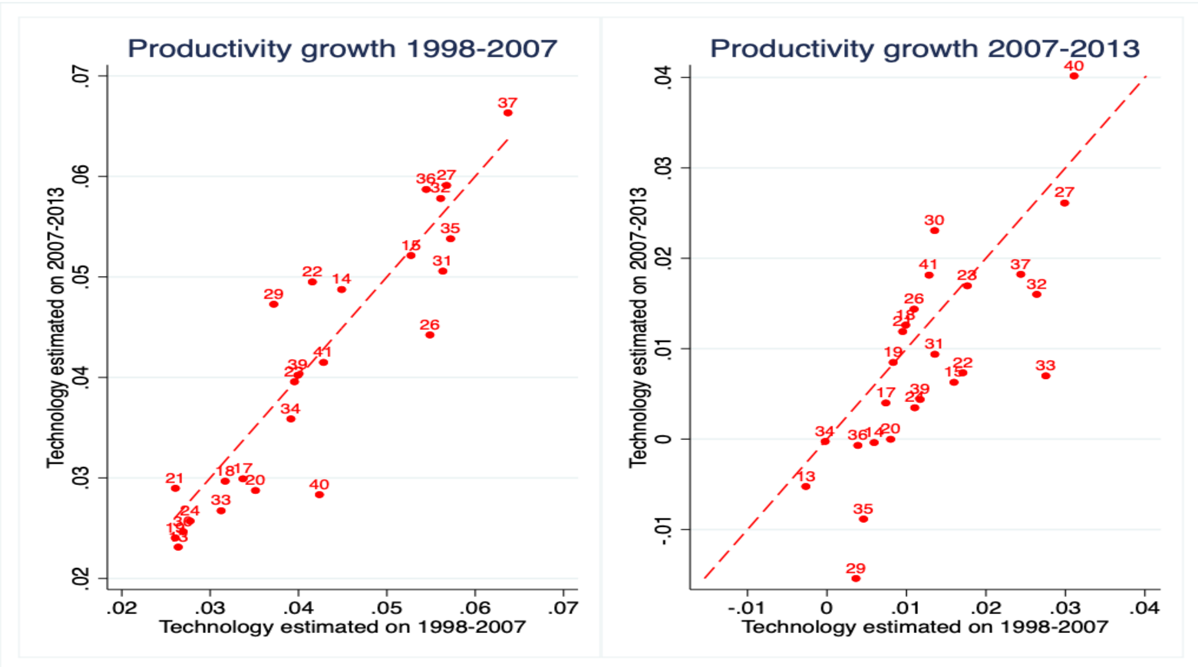
Notes: The box plots summarize the distributions of relative productivity of young firms versus incumbents across 2-digit industries, separately for each ownership category. The productivity level of the average incumbent in the industry across all ownership types is always used as reference. The shaded box represents the inter-quartile range, and the vertical line in the box the median. The simulated samples are based on the time-varying weighting function.

Figure B.6: Alternative TFP growth estimates by industry

(a) Constant weighting function



(b) Time-varying weighting function



Notes: The two graphs on the left show 2-digit industry-level productivity growth estimates for 1998-2007 (using input and output information from the NBS data) calculated in two ways. Results on the horizontal axis use production function parameters estimated on the same period, while results on the vertical axis use production function parameters estimated using the simulated sample on the 2007-2013 period. Graphs on the right show productivity estimates on the simulated data for 2007-2013 based on the same two sets of production technology parameters. Panel (a) uses the constant weighting function to simulate samples; Panel (b) uses the time-varying weighting function.