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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 years from 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 using 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 those 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 estimates at a more aggregate level, and to identify the sources of change in productivity growth. 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 1998-2013. 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 baseline estimates, which are likely to be an upper bound, suggest TFP growth of 1.4 percent between 2007-2013, about 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.[3] Although some of this reduction occurs among incumbent firms, far more important is the dissipating 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). At the end, we discuss several explanations for the secular decline in productivity growth.

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.

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). 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

[3]The firm-type classification is highly detailed, but we group them into four broad categories: state-owned firms, other domestic Chinese firms, Hong Kong, Macau and Taiwan firms, and foreign-invested firms.

manufacturing industry.[4]

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 sales 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.[5]

After 2007, data issues make the NBS sample less credible and useful, especially if the objective is to compare results over time.[6] 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 always included.[7] *Sampled firms* are selected from the universe of all remaining active

[4] 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.

[5] 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.

[6] 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.

[7] 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,

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.[8] 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.[9] 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 results in an under-reporting of revenue in the STA data.[10]

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 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.

exporters that pay VAT, and listed firms with a major business subject to VAT.

[8] Although we have access to the STA data up to 2015, we did 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, there was change in the sampling frame for the STA data between 2013 and 2014. After 2014, sampling of focus firms is reduced even further. Only 40 percent of the firms in the 2013 STA data are sampled again in 2014.

[9] 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.

[10] This 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.

Table 1: Coverage of the NBS and STA samples

Year	(a) NBS survey				(b) STA survey				
	No. of firms	Above scale (%)	New in sample (%)	Matched w/ STA (%)	No. of firms	Above scale (%)	New in sample (%)	Matched w/NBS (%)	Above & Unmatched (%)
2007	312,055	98.1	18.2	35.1	196,726	40.9	-	41.1	11.5
2008	381,451	97.8	29.0	34.1	224,539	41.4	28.3	43.3	13.5
2009	361,600	98.3	10.7	33.2	278,992	49.4	29.8	40.9	18.2
2010	-	-	-	-	290,408	55.7	36.5	-	-
2011	278,568	98.6	-	43.7	266,806	44.0	25.9	45.3	9.4
2012	287,159	98.3	12.8	43.0	256,474	48.0	28.4	48.5	10.6
2013	318,828	98.7	18.3	40.4	247,810	48.5	21.1	52.3	9.1

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.

As for their direct impact on TFP growth measures, 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.[11] 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 any 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 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 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 STA sample

[11]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 the business tax system to the VAT system in the service sector (2012).

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

Year	No. of firms	(a) Paid-in Capital p10	p25	p50	p75	p90	(b) Fixed Assets p10	p25	p50	p75	p90
2007	86,313	0.66	1.00	1.00	1.00	1.01	0.42	1.00	1.00	1.00	1.03
2008	99,771	0.50	1.00	1.00	1.00	1.00	0.25	0.86	1.00	1.00	1.01
2009	108,275	.	.	.	.	.	.	.	.	.	.
2011	102,123	0.56	1.00	1.00	1.00	1.17	0.20	0.74	1.00	1.00	1.03
2012	114,299	0.57	1.00	1.00	1.00	1.05	0.12	0.69	1.00	1.00	1.01
2013	100,308	0.34	1.00	1.00	1.00	1.00	0.11	0.63	1.00	1.00	1.01
		(c) Output p10	p25	p50	p75	p90	(d) Employment p10	p25	p50	p75	p90
2007		0.12	0.51	1.00	1.00	1.07	0.50	0.86	1.00	1.05	1.31
2008		0.05	0.23	0.82	1.00	1.21	0.42	0.79	1.00	1.04	1.27
2009		0.07	0.28	0.86	1.00	1.12	0.39	0.78	1.00	1.05	1.40
2011		0.09	0.32	0.91	1.00	1.04	0.20	0.37	0.62	0.88	1.29
2012		0.08	0.31	0.91	1.00	1.04	0.19	0.36	0.60	0.87	1.39
2013		0.07	0.27	0.88	1.00	1.03	0.20	0.38	0.69	1.14	1.74
		(e) Value-added Tax p10	p25	p50	p75	p90	(f) Profit p10	p25	p50	p75	p90
2007		0.13	0.62	0.96	1.03	1.26	-/+	0.13	1.00	1.00	1.20
2008		0.07	0.42	0.95	1.04	1.23	.	.	.	.	.
2009		0.02	0.31	0.93	1.05	1.53	.	.	.	.	.
2011		0.01	0.24	0.90	1.02	1.24	-/+	0.02	0.85	1.00	1.10
2012		0.00	0.19	0.90	1.02	1.23	.	.	.	.	.
2013		0.01	0.19	0.89	1.01	1.21	.	.	.	.	.

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. Profit is only reported in 2007 and 2011 in the STA survey. The −/+ indicated for the 10th percentile ratio means that these firms report a loss in one survey and a profit in the other.

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.[12]

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 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.

Information on paid-in (registered) capital is most consistently reported, with more than 65% of matched firms in some years 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 also equals one in 2007, but falls to 0.63 by 2013. Over time, over-reporting in the NBS survey becomes a more serious problem for firms in the lower half of the distribution. Even larger differences between the two surveys appear for output and employment. When values differ, they are more likely to be reported higher in the NBS survey, especially for firm output. But for both variables, the ratios at the 90th percentile are above one, indicating that a sizable fraction of firms report larger values in the STA survey. Over time, the ratios in the lower percentiles fall, indicative of widening over-reporting in the NBS data.[13]

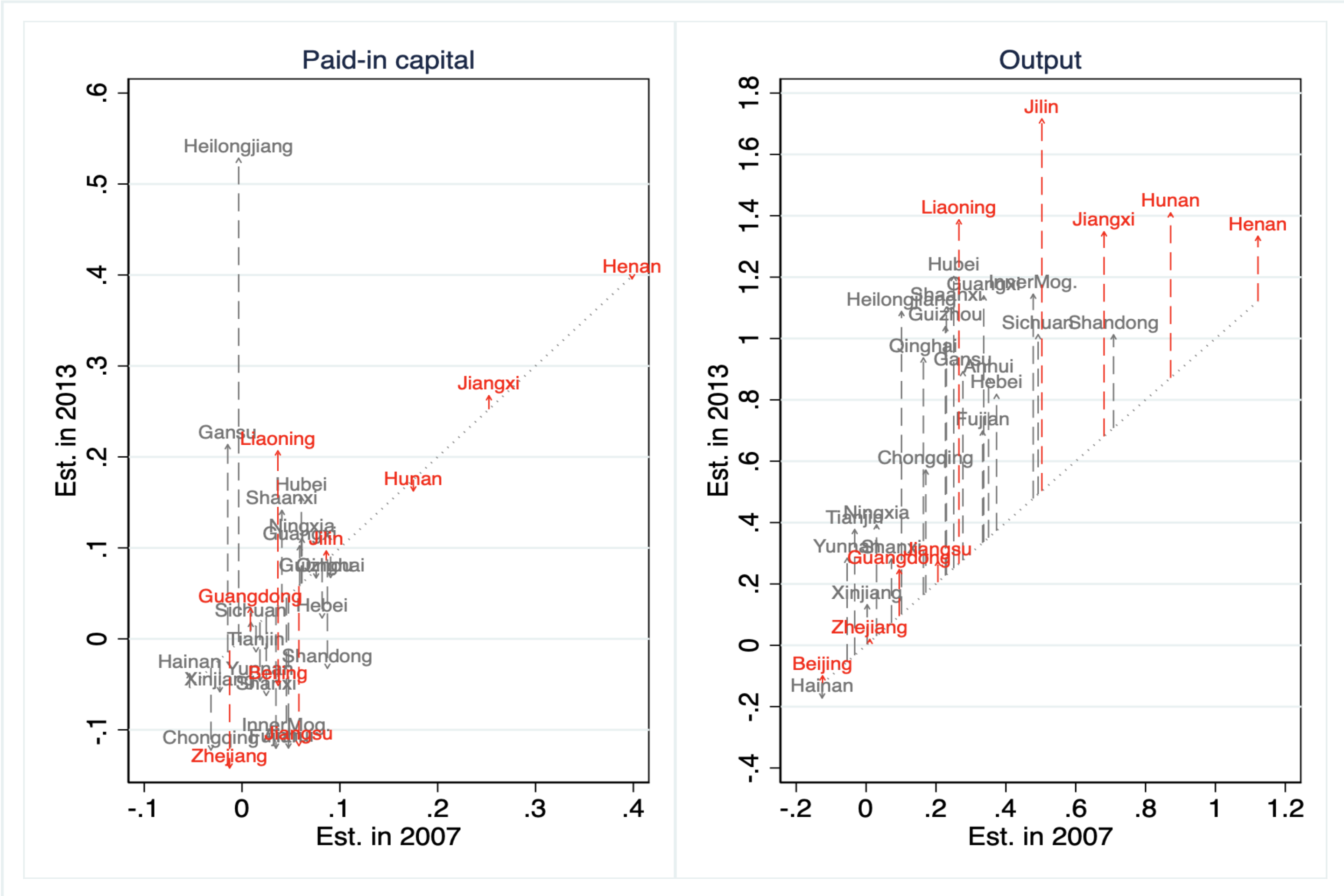
In Figure 1 we plot coefficients from OLS regressions of the log differences in the values reported in the two surveys for firm output and paid-in capital on a set of dummy variables for province, ownership type and 2-digit industry. The regressions are run separately for each year, but we only show the estimates for 2007 and 2013. Along each dimension we pick 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. The intercepts for the discrepancy in paid-in capital, which is the average value of a foreign firm in industry 37 from Shanghai, are 0.110 and -0.079 for 2007 and 2013, respectively, and -0.051 and 0.035 for output. Especially for output, much of the discrepancies can be explained by these observables.[14] Panel (a) shows provincial differences and Panel (b) shows differences across ownership types.

[12]In 2013, for example, (49-9)/49 = 81.6 percent of firms can be matched.

[13]The output discrepancies are especially large in 2008 and in later analysis we will often omit that year as it appears uniquely subject to measurement errors.

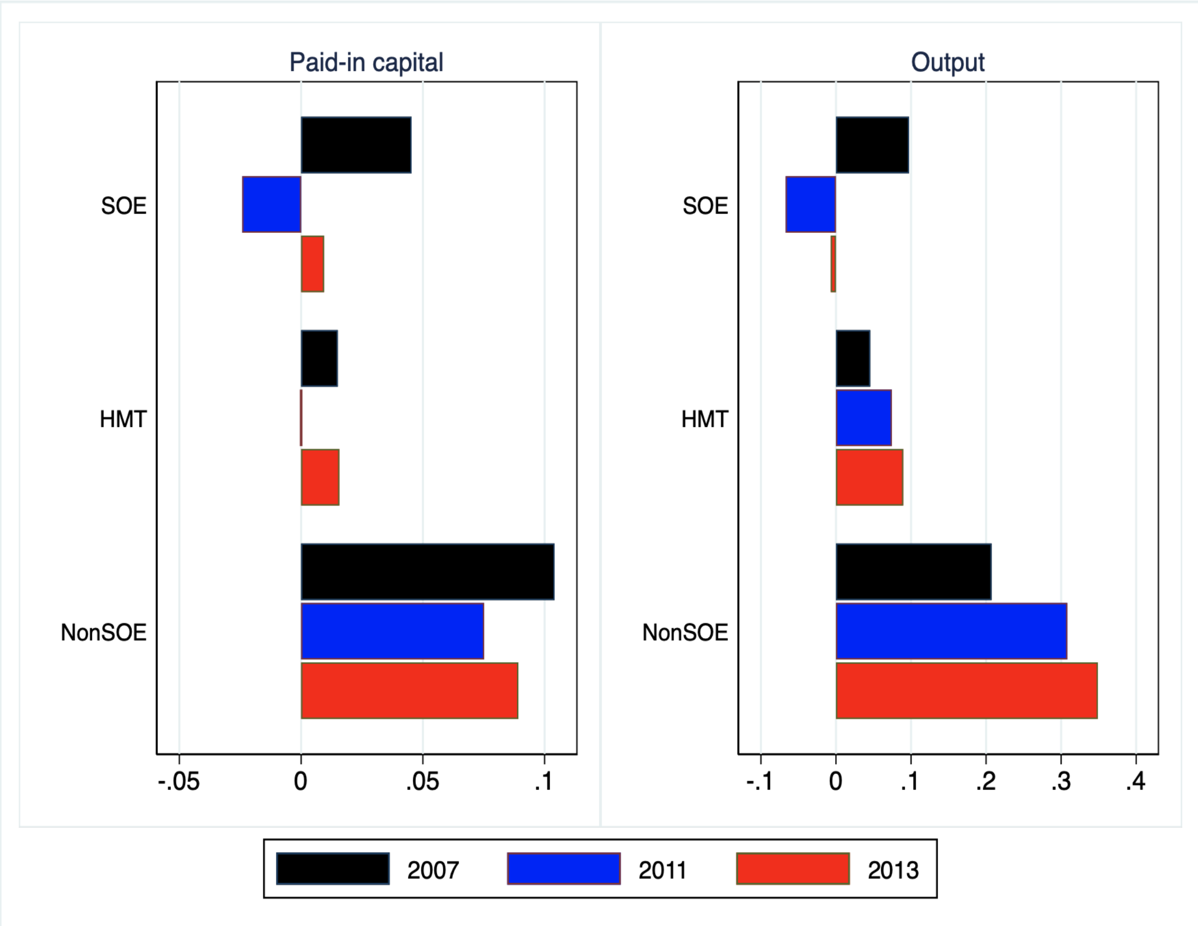
[14]The patterns are similar on the matched sample of firms appearing in both the NBS and STA data in both 2007 and 2013, a total of 24,128 firms. The discrepancy in output rises from 22% to 39% and for paid-in capital from 4% to 10%. Restricting the sample to firms located in Shanghai (940 firms), the 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%.

Figure 1: Patterns in the reporting discrepancies
(a) Discrepancy by province



Notes: Markers represent all provinces in mainland China. Arrows indicate the change in discrepancy from 2007 to 2013 relative to the change in Shanghai. Provinces highlighted in red are those with either consistently low output discrepancy or very higher discrepancy by 2013.

(b) Discrepancy by ownership type



Notes: Discrepancy measures are obtained as coefficients on province dummies (Shanghai as reference) and 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 (CIC 37 as reference).

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.[15] 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

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

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 sample, which is representative of the population, to weight observations in the STA sample so that the resulting sample is both reliable and representative. We construct two possible weighting functions, one that relies on observing the target NBS population in 2007 and a second that requires several variables that are reported accurately in the NBS sample in later years. We can then construct a weighting factor based on the discrepancy between the distributions of those variables in the two samples.

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 aspect 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:

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

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:

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

where

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

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, as 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 $(k, \mathbf{z}, \mathbf{A})$ that predict the probability of appearing in the source sample in the same way as variables $(y, \mathbf{x}, \mathbf{A})$, i.e.,

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

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

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

A similar equation applies conditioning on the $(k, \mathbf{z}, \mathbf{A})$ variables, such that

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

Assumption (4) then implies that the target density ratio can be expressed in two equivalent ways, i.e., $r_t(y, \mathbf{x}, \mathbf{A}) = r_t(k, \mathbf{z}, \mathbf{A})$. 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

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

To estimate the size-weighted average productivity conditional on attributes $A = \mathbf{a}$ for a subgroup of firms, we can rely on the same ratio of unconditional densities and adjust for the relative frequency of the subgroup in the two samples. Let $\mathbf{v}$ represent $(y, \mathbf{x})$ or $(k, \mathbf{z})$ for either density ratio approach. The productivity for the subgroup is then:

$$\begin{aligned} m_t^T(y, \omega^*(\mathbf{A})|\mathbf{A}{=}\mathbf{a}) &= \int_{\mathbf{v}} g(y, \mathbf{x}, \mathbf{a}) \frac{f^T(\mathbf{v}, \mathbf{a})}{Prob^T(\mathbf{A} = \mathbf{a})}\, d\mathbf{v} \\ &= \int_{\mathbf{v}} g(y, \mathbf{x}, \mathbf{a}) \frac{r_t(\mathbf{v}, \mathbf{a}) f^S(\mathbf{v}, \mathbf{a})}{Prob^T(\mathbf{A} = \mathbf{a})}\, d\mathbf{v} \\ &= \int_{\mathbf{v}} g(y, \mathbf{x}, \mathbf{a})\, r_t(\mathbf{v}, \mathbf{a}) \frac{Prob^S(\mathbf{A} = \mathbf{a})}{Prob^T(\mathbf{A} = \mathbf{a})} f^S(\mathbf{v}, \mathbf{A}|\mathbf{A} = \mathbf{a})\, d\mathbf{v}. \end{aligned} \tag{6}$$

3.2 Estimation of 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 from Kanamori, Hido, and Sugiyama (2009).

Denote the true density-ratio function that we want by $r^*(\mathbf{v}) = f^{T^*}(\mathbf{v})/f^{S^*}(\mathbf{v})$. The estimate will be the function $r()$ 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

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

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 Estimation of 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. 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.[16] It uses only information from 2007 for both the source (STA) and target (NBS) samples.

The estimation of the time-varying density ratio function keeps k in $\mathbf{x}$, the real

[16] We include the province, ownership type, and firm age.

capital stock calculated for each year in the two samples, and replaces y and other input variables in $\mathbf{x}$ with $\mathbf{z}$, a vector of firm-level variables that do not directly enter the production function, which include the wage bill, fixed assets at original purchase price, paid-in capital, export status and export value. We keep the real capital stock k because of relatively small differences in reporting between the two surveys.

We use Gaussian kernels for the basis functions $\phi()$ and take 1000 Gaussian centers $\mathbf{c}$ from the combination of $\mathbf{v}^S$ and $\mathbf{v}^N$.[17] In the time-invariant density function, we estimate combination weights β with the 2007 data and apply the same function to STA observations of all years to construct the weights. In the time-varying density function, we separately estimate combination weights β for each year and use them to construct weights for the STA observations in the same year.

3.3.2 Data issues

A careful examination of the data reveals more serious measurement error in the STA data for 2008 than in other years. One indicator is the significantly lower year-to-year correlation of firm-level (log) output values over 2007-2008 (0.72) and 2008-2009 (0.76) than in other years of the STA sample as well as the NBS sample for 1998-2007 (averaging 0.90). As a result, we exclude 2008 from the estimation and analysis.

Other data shortcomings require modifications in how we implement the time-varying weighting scheme. First, since output information in the NBS survey becomes less accurate over time, we cannot reliably split the NBS sample into size categories after 2007 to match the stratified sampling scheme by STA. Thus, we estimate for each year for which we have NBS data, i.e., 2011, 2012 and 2013, a weighting function based on the full NBS sample and the set of firms in the STA sample with revenue above 20 million RMB. This density function is then used to simulate the sample above 20 million RMB. Second, the size threshold for inclusion in the NBS survey was raised from 5 to 20 million RMB in 2011. Without data on sales below 20 million RMB for these years, we apply the 2007 weighting function for this size category in other 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. Since we cannot estimate a separate weighting function for 2009 and 2010, we apply the weighting function estimated on 2007 data to the STA data for these two years.

In summary, our first strategy is to estimate and apply the 2007 time-invariant weighting function based on input, output and productivity shifter variables, to all years separately for the three size categories by industry cells to predict sampling

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

weights. The second strategy is to apply a year-specific or time-varying weighting function based on a different set of variables to 2007 and 2011-2013, but distinguishing only two size categories (threshold at sales of 20 million RMB) in the specification of the density function for the last three years.[18] For all firms in 2009 and 2010, as well as for the smallest size category in all years, i.e., firms with sales between 5 and 20 million RMB, we use the 2007 density function to predict weights.

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 sales between 5-20 million RMB. Moreover, inflated values for firm output may bias the breakdown over the three size categories.

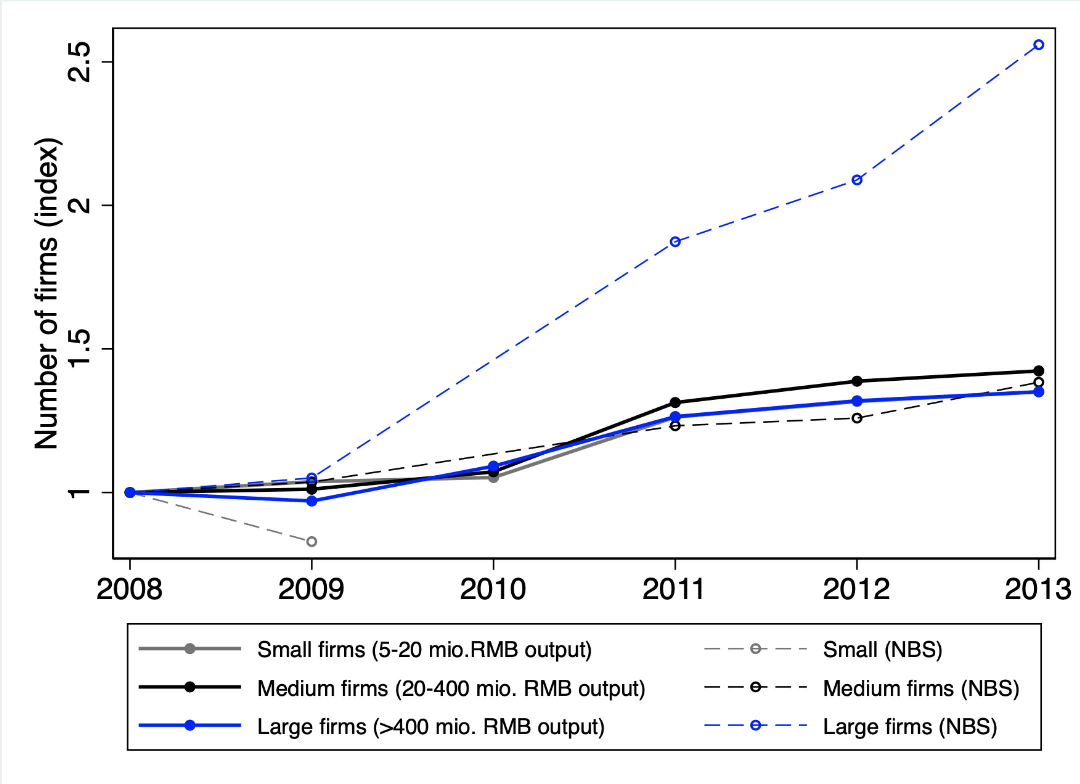
We leverage the State Administration for Industry and Commerce's (SAIC) Business Registry and the annual Inspection Data to determine for each year the number of firms in each of the three size categories.[19] Our starting point is the number of firms in each size category in the NBS data for 2008, a 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 the percentage in each size category and the total number of above-scale firms reported in the NBS Statistical Yearbook. Further details are provided in Table A.1 in the Appendix.

Figure 2 reports the growth in the number of firms by size category in both the original NBS data (dashed lines) and our alternative estimates (solid lines). Between 2008 and 2013, the NBS data shows an implausibly large increase in the number of large firms (with sales above 400 million RMB). By comparison, our alternative estimates suggest similar rates of growth in the number of firms across all three size categories. As shown in Table A.1, by 2013 the number of large firms in the NBS sample is 70% larger than the estimates based on our alternative data.

[18]While the weighting function is the same for firms with annual sales of 20-400 or 400+ million RMB, the number of firms to simulate is still decided separately for both groups, which is discussed in the next section.

[19]For regulatory purposes, SAIC collects annual information on all firm's assets, liabilities, total sales, 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: The solid lines represent an index (2008=1) for the number of firms in the simulated samples for the three size categories. These are predicted based on three data sources (see text). The dashed lines show the evolution of the number of firms in the NBS sample.

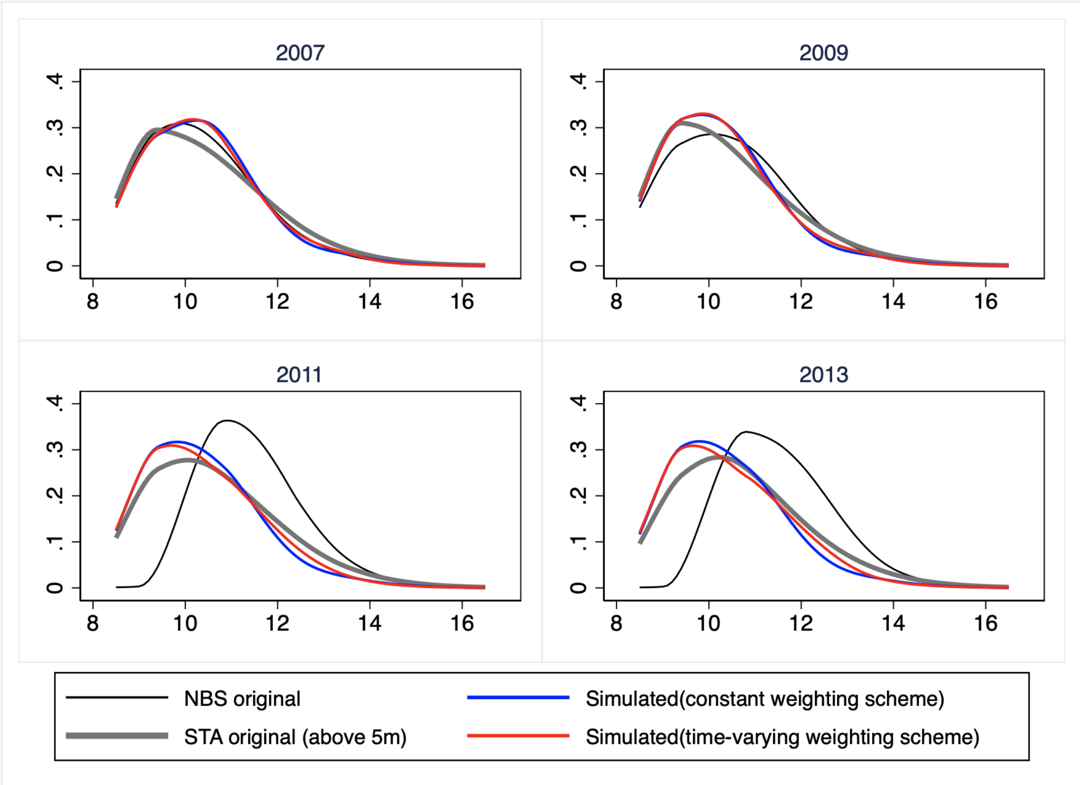
3.3.4 Sample simulation

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 is discussed in Section 3.3.3.

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

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

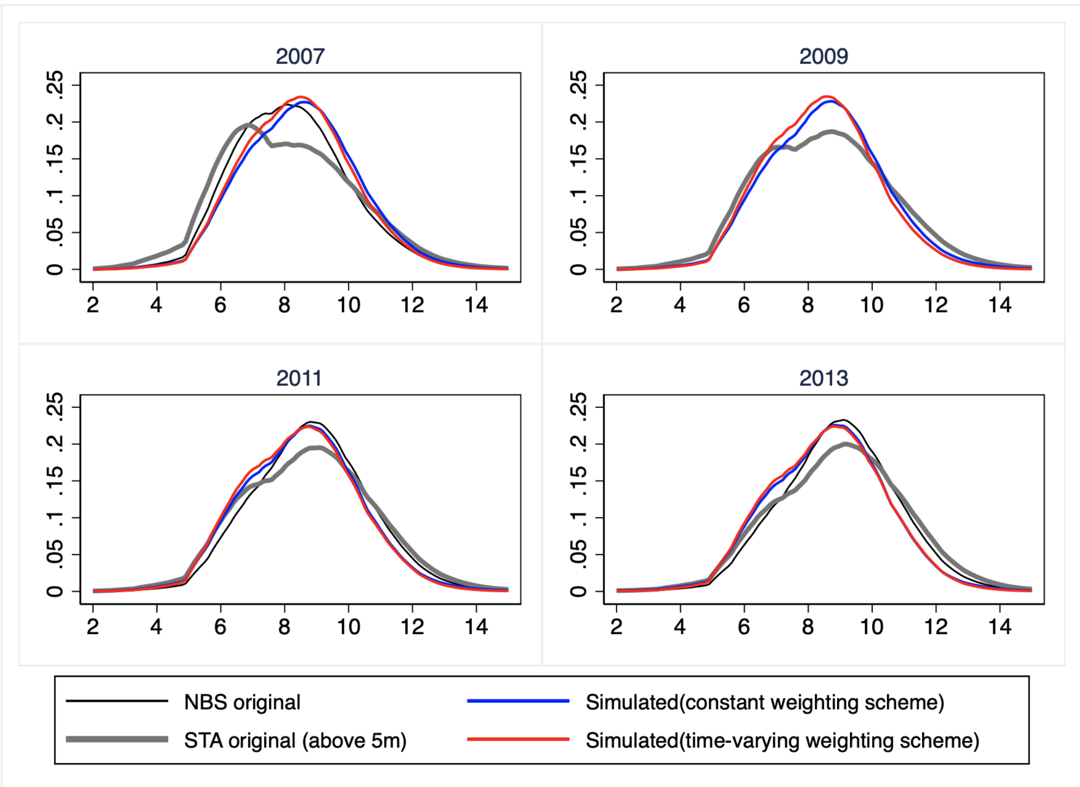


Table 3: Annualized growth rates of output and input variables (2007-2013)

	Value added (nominal)	Gross output (nominal)	Employment (persons)	Capital (real)
NBS above-scale survey		15.4	11.3	13.6
NBS Yearbook (above-scale)	12.0	15.9	3.6	15.1
STA unweighted	10.8	13.4	0.6	9.8
Simulated (constant weights)	9.4	11.0	3.6	10.2
Simulated (time-varying weights)	10.3	11.9	3.9	13.2

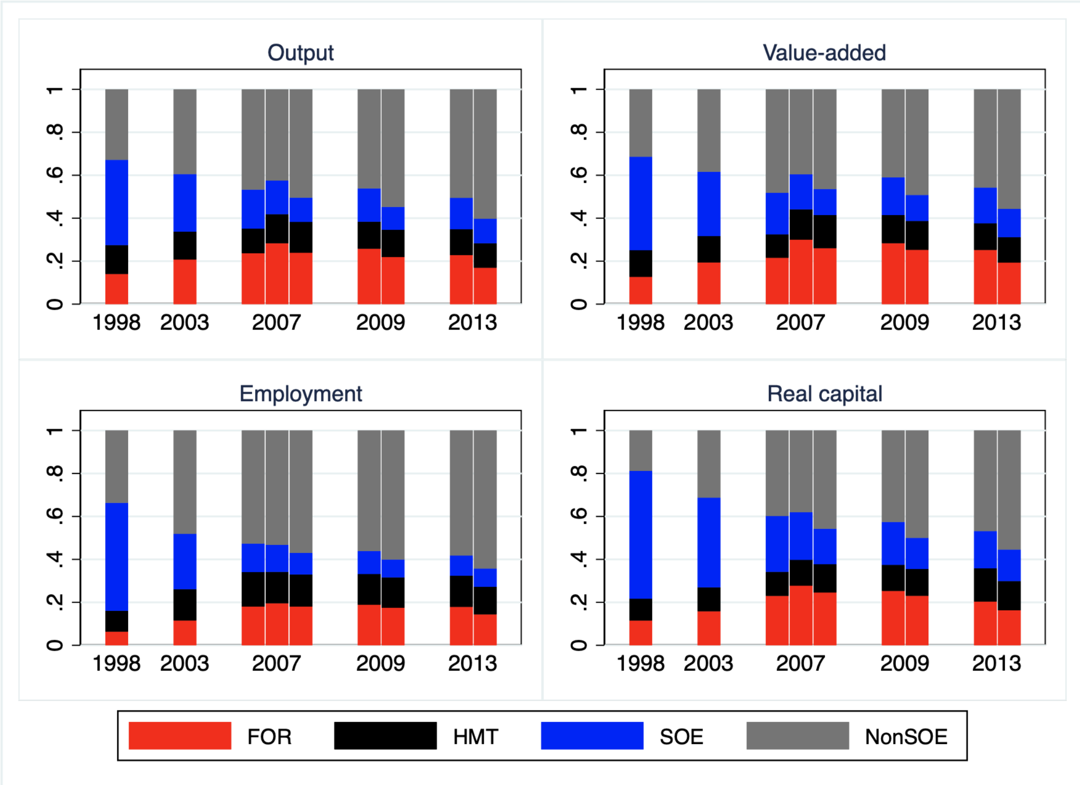
Notes: For the firm-level samples, we first aggregate variables for all manufacturing firms by year and then calculate a single annualized growth rate over the full period. Value added and gross output are in current prices, and capital is in real values constructed using a perpetual inventory method (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 total asset value. The NBS Yearbook reports a growth in industrial GDP for all firms, not limited to above-scale firms, of 11.5%.

is fairly stable. It only shifts gradually to the right over time. 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 with only a single set of weights to sample firms from the full STA sample, we are able to match the very distinct patterns and evolution of the densities of two variables.

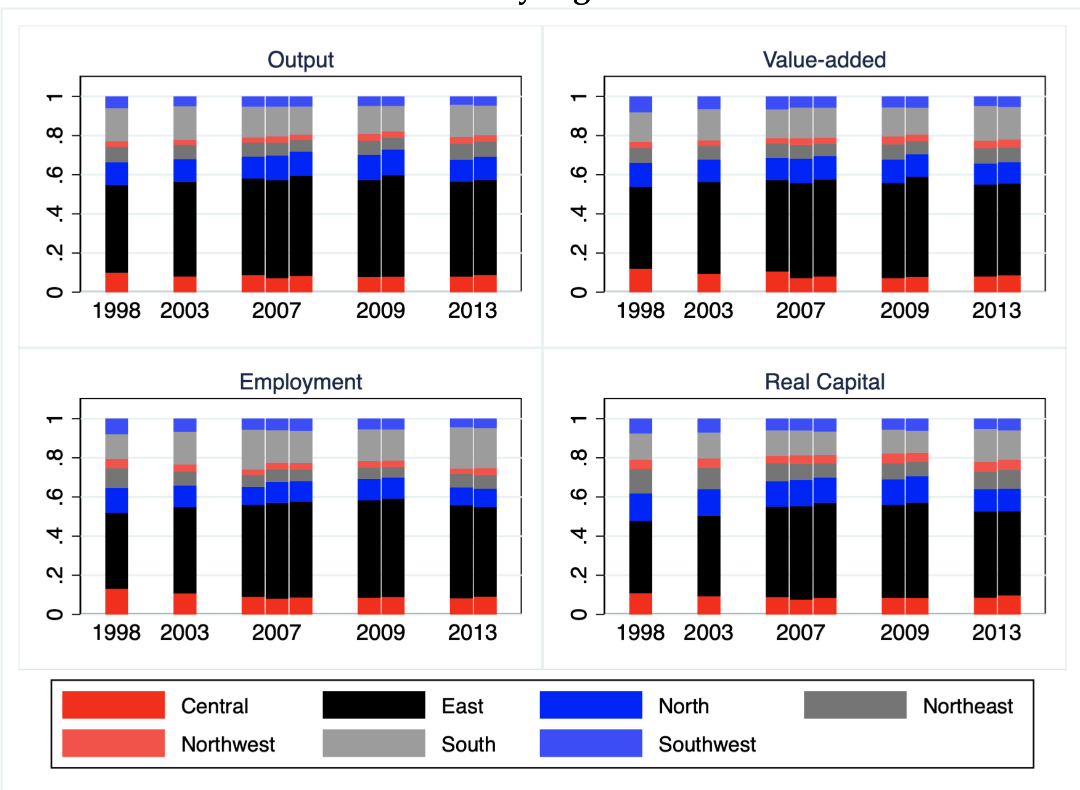
In Table 3, we report the growth rates of value added, gross output, employment and real capital for the period 2007-2013 for the same four samples. We also show the growth rates based on aggregates for the same set of firms as reported in the Statistical Yearbook. Consistent with our earlier discussion, 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 13.4% in the STA data, and 13.6% versus 9.8% in the case of capital. Applying either weighting scheme to samples from the STA survey reduces the growth rate of gross output by 1.5 to 2.5 percent per annum, but raises the growth rates for employment and capital. Growth rates for employment and real capital for the simulated samples are similar to 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

Figure 4: Sample composition in the different samples
(a) By ownership type



(b) By region



Notes: The single bar in 1998 and 2003 is for the NBS sample. The three bars in 2007, from left to right, correspond to the NBS sample, the simulated sample with the constant weighting scheme, and the one with the time-varying weighting scheme. The two bars in 2009 and 2013 are based on simulated samples, the constant one on the left and the time-varying one on the right.

sector. By 2013, the non-state is the source of nearly sixty percent of output and employment in manufacturing. The role of foreign firms grows between 1998-2007, but then begins to retreat for every variable. In comparison, changes in the regional composition of industrial activity are barely noticeable.

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:

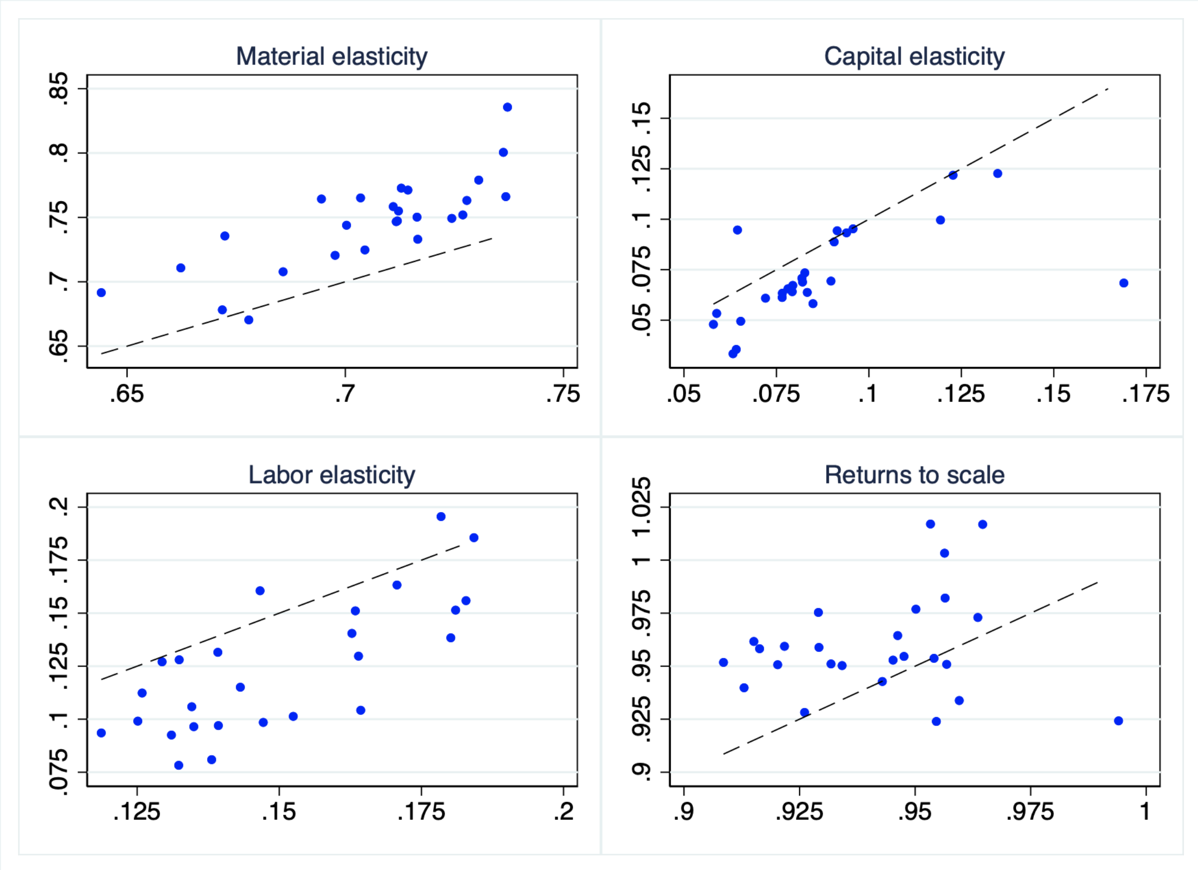
$$y_{it} = f(k_{it}, l_{it}, m_{it}) + \omega_{it} + \varepsilon_{it} \qquad \text{with } \omega_{it} = \rho\omega_{it-1} + \eta_{it}. \tag{7}$$

The deterministic part is a nonparametric input-aggregator $f(\cdot)$. 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 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.[20] 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)

[20]The benchmark estimates are based on the simulated samples obtained using the constant weighting function. Results based on the time-varying 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.

Figure 5: Output elasticities estimated on two periods

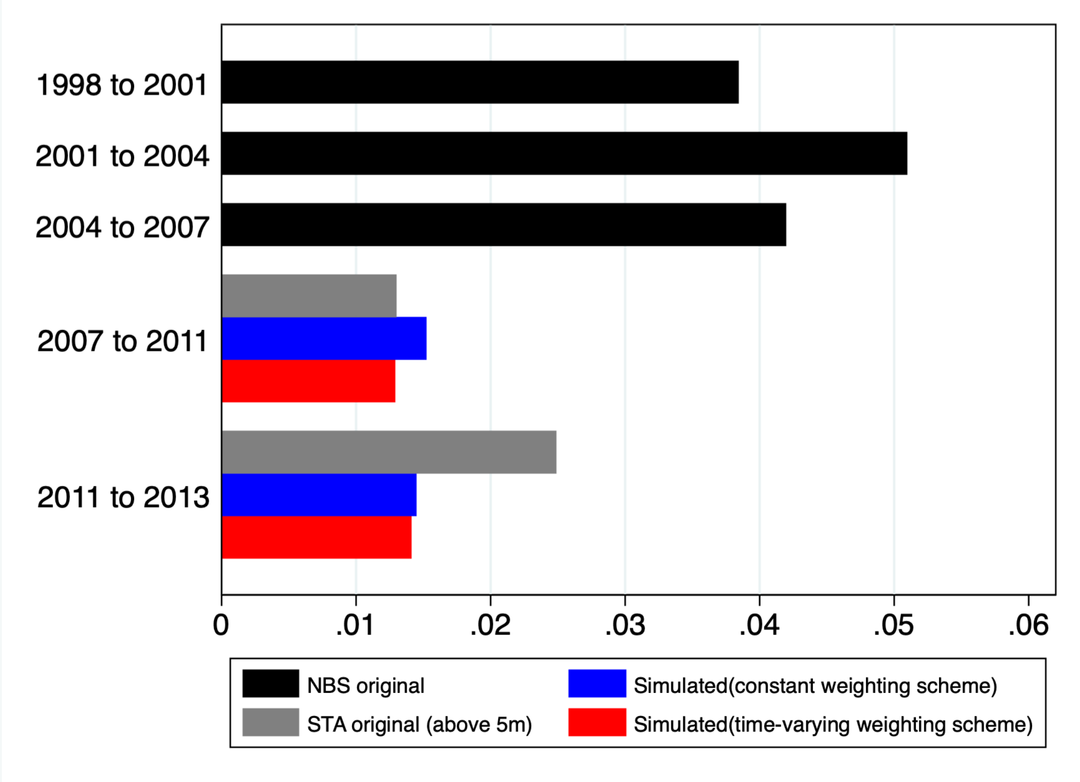


Notes: Three panels show the output elasticities for all three inputs estimated using a non-parametric production function. The horizontal axis shows the estimates for 1998-2007 on the NBS data and the vertical axis the estimates for 2007-2013 on the simulated samples with a constant weighting function. 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 industry. The dashed line is the 45-degree line. Results based on a time-varying weighting function are in Figure B.1 in the Appendix.

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.

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.

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



5. Results

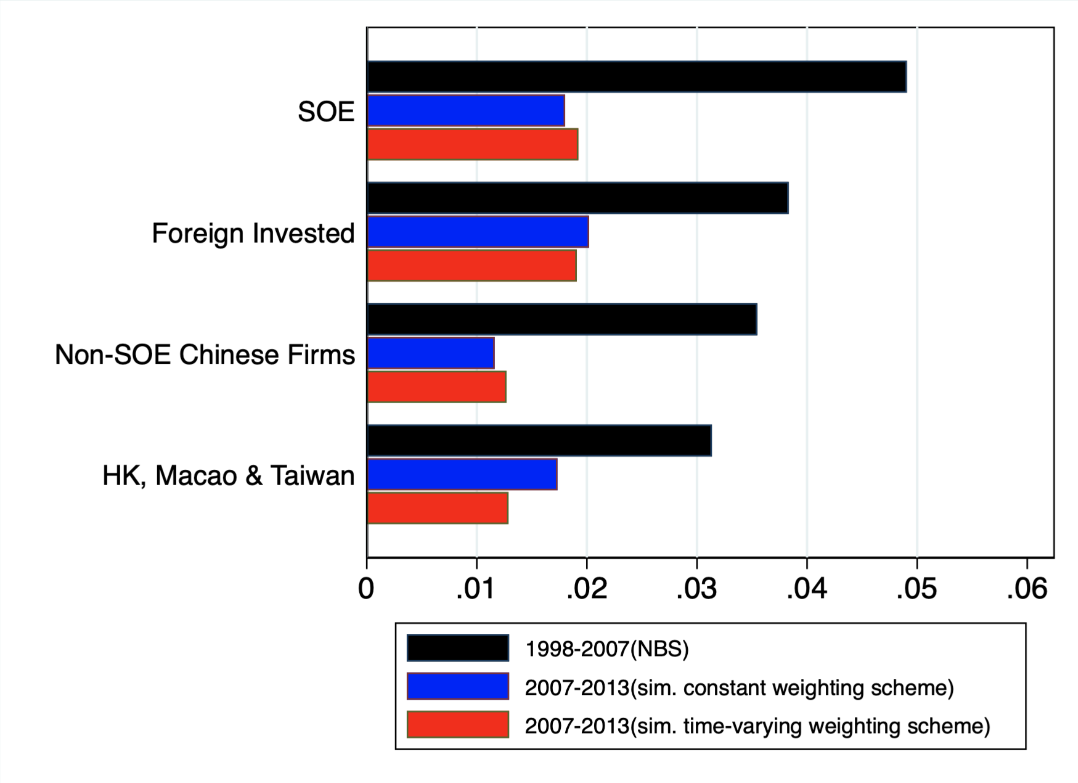
We calculate firm-level productivity $\widehat{\omega}_{it}$ as a residual from the production function (7) and aggregate to the industry-level productivity $\widehat{\Omega}_t = \sum_i s_{it}\widehat{\omega}_{it}$, using output shares as weights. Annualized productivity growth for the entire Chinese 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.[21] One reason for this is that the GNR method estimates diminishing returns to scale in all industries, as shown in Figure 5. 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 produces lower productivity growth estimates.

For the later periods, 2007-2011 and 2011-2013, three sets of results are shown.[22]

[21]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.

[22]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

Figure 7: Productivity growth by ownership type



The statistics shown in gray use the original STA sample, limited to firms with annual output above 5 million RMB. The results in blue and red are the averages over 5 simulated samples obtained using either constant or time-varying weighting functions. The estimates based on the simulated, representative samples are very similar. They both imply a significant slowdown after 2007, with productivity growth between 2007-2013 approximately a third of the growth rate between 1998-2007.

Results for year-on-year growth rates are reported in Figure B.2 of the Appendix. These estimates show broadly the same pattern, but exhibit more volatility, especially after 2007. For example, productivity growth declines sharply between 2007 and 2009 during the Great Recession, followed by an even stronger stimulus-fueled recovery. 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 differences in productivity growth by ownership for the two periods. Between 1998-2007 state-owned enterprises performed most strongly, reflecting the

be calculated in that year.

benefits of restructuring and downsizing (Hsieh and Song, 2015). During this period, their share of value added declined from 42% to 20% as the state retreated from more labor-intensive industries where it had no comparative advantage. All other ownership categories show robust productivity growth of at least 3% per annum.

After 2007, productivity growth declined significantly for firms in every ownership category. SOEs, whose share of manufacturing value added continued to decline between 2007-2013, experienced the largest absolute decline in productivity growth. Outside the state sector, private (non-SOE Chinese) firms experienced the largest decline, with productivity growth only one-third of the pre-2007 growth rate. Private firms experienced the lowest productivity growth of all ownership types, averaging only slightly more than one percent. Estimates of productivity growth based on the two weighting schemes are very similar for each ownership type.

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

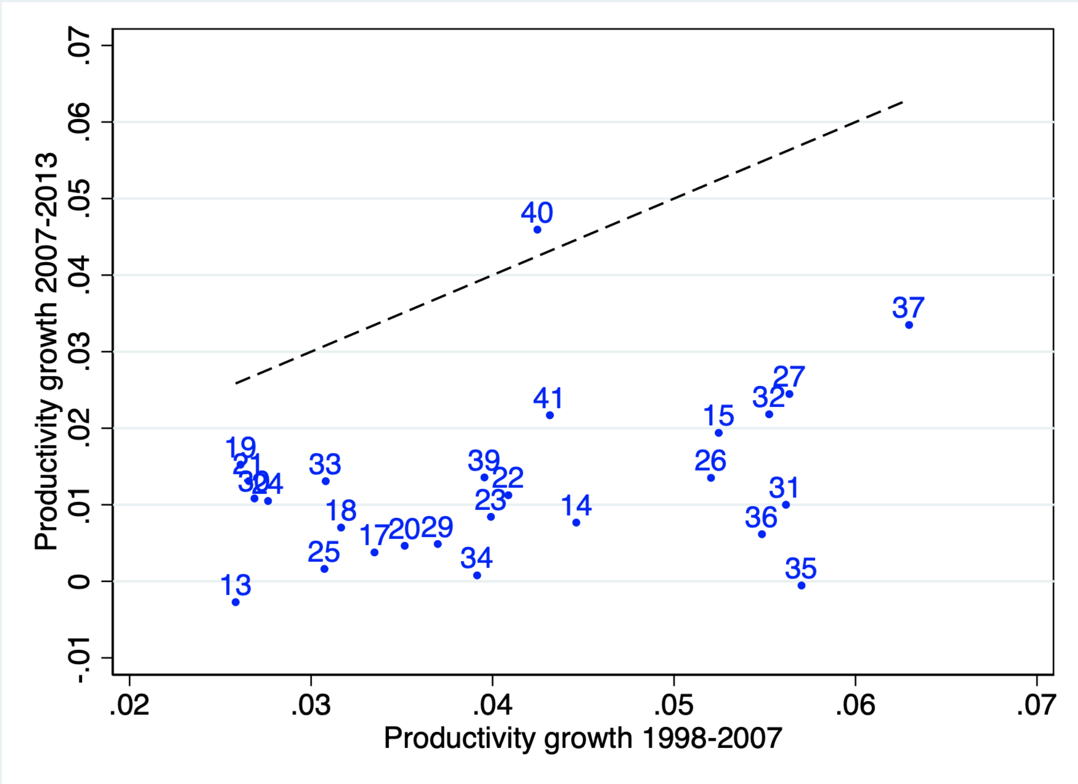
5.1.2 Industry

Figure 8 shows productivity growth rates for the 26 2-digit industries for the two periods.[23] 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% 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., Petroleum (CIC 25), Metal Products (CIC 34), General 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 CIC 26, 35, 36 and 39 account for a particularly high share of

[23] Because of their small sample sizes, we exclude Tobacco (CIC 16), Chemical Fibre (CIC 28), Weapons and Ammunition (CIC 38), and a miscellaneous category (CIC 42) from the figure.

Figure 8: Productivity growth by industry



Notes: The results for 2007-2013 use samples simulated with a constant weighting function. Results based on a time-varying 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.

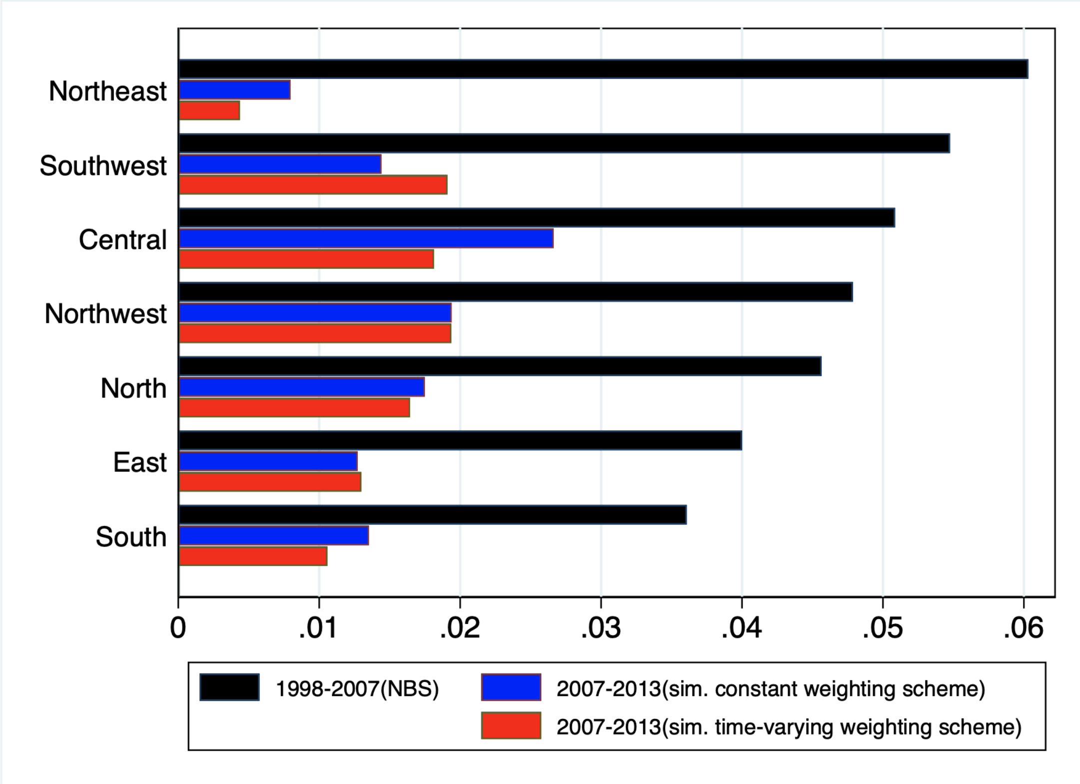
all invention patents by China's manufacturing sector between 2001-2013 (Wu, Lin, and Wu, 2022).

5.1.3 Region

Figure 9 captures stark differences in productivity growth rates across regions. Between 1998-2007, they were highest 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 lowest 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, and 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 through 2007 (Brandt and Lim forthcoming).

Productivity converged across regions as a result of this behavior. Figure 10 plots TFP growth against initial TFP at the province-industry level for the periods 1998-2007 and 2007-2013. Each point represents an industry by province pair. The negative slopes of the two regression lines indicate rapid convergence in productivity

Figure 9: Productivity growth by region



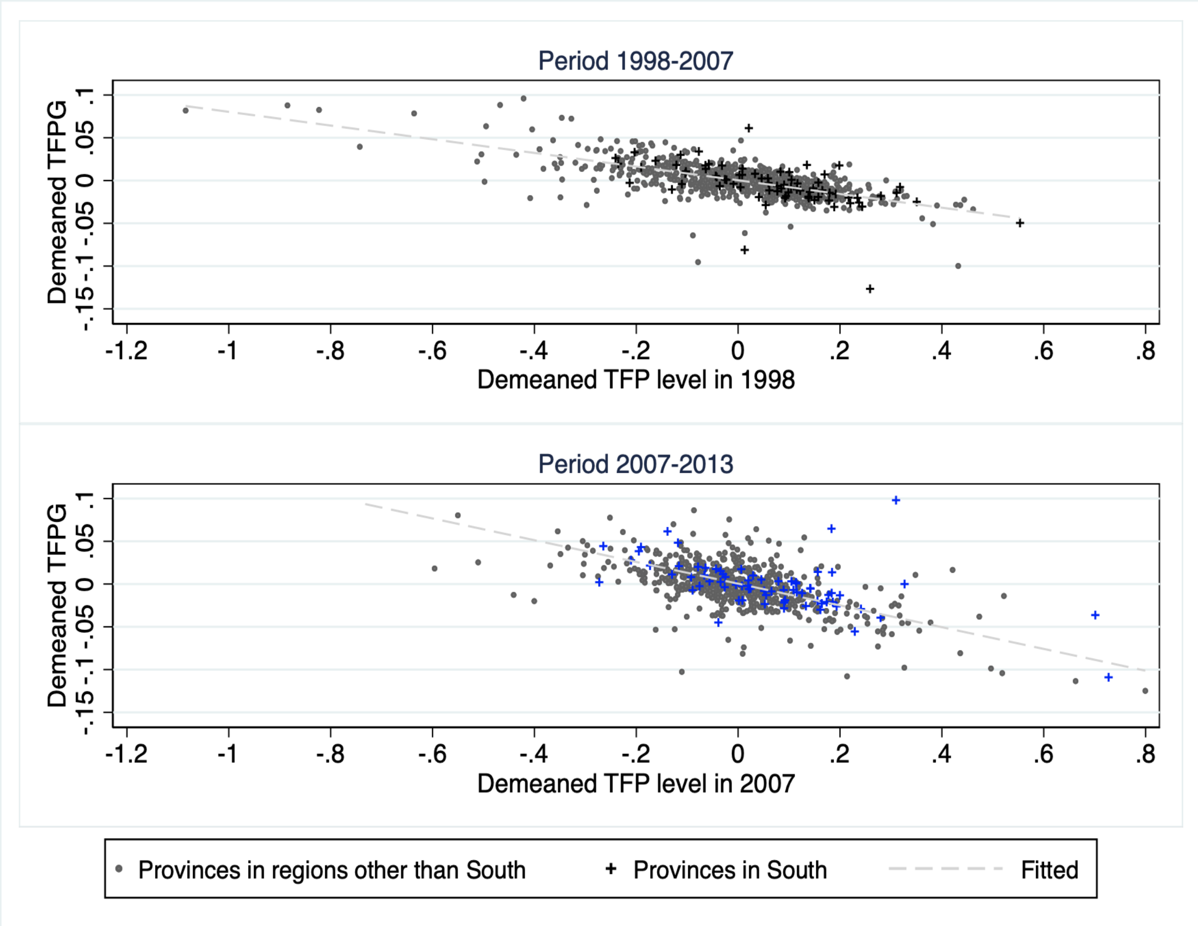
across provinces within industries. The rate of β-convergence is 6 percent between 1998 to 2007, and 9 percent from 2007 to 2013 using the constant weighting function. A β-convergence rate of 7 percent implies that it takes 10 years to halve an initial gap in TFP in levels between two provinces.[24]

Convergence can be an important source of TFP growth, but by itself is not revealing of productivity growth rates in the sector. After 2007, regional differences continued to narrow, however this largely reflected lackluster TFP growth in the leading 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 outside the coast.

Figure 11 shows the evolution of the gap between each region's TFP level relative to the South, the reference province. Our estimates suggest there is limited room left for regional convergence as a future source of TFP growth. In most regions, the gap with the South declines significantly over time. By 2013, the average remaining gap is only 5 percent of the South's TFP level.

[24]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 10: Persistent productivity convergence across provinces

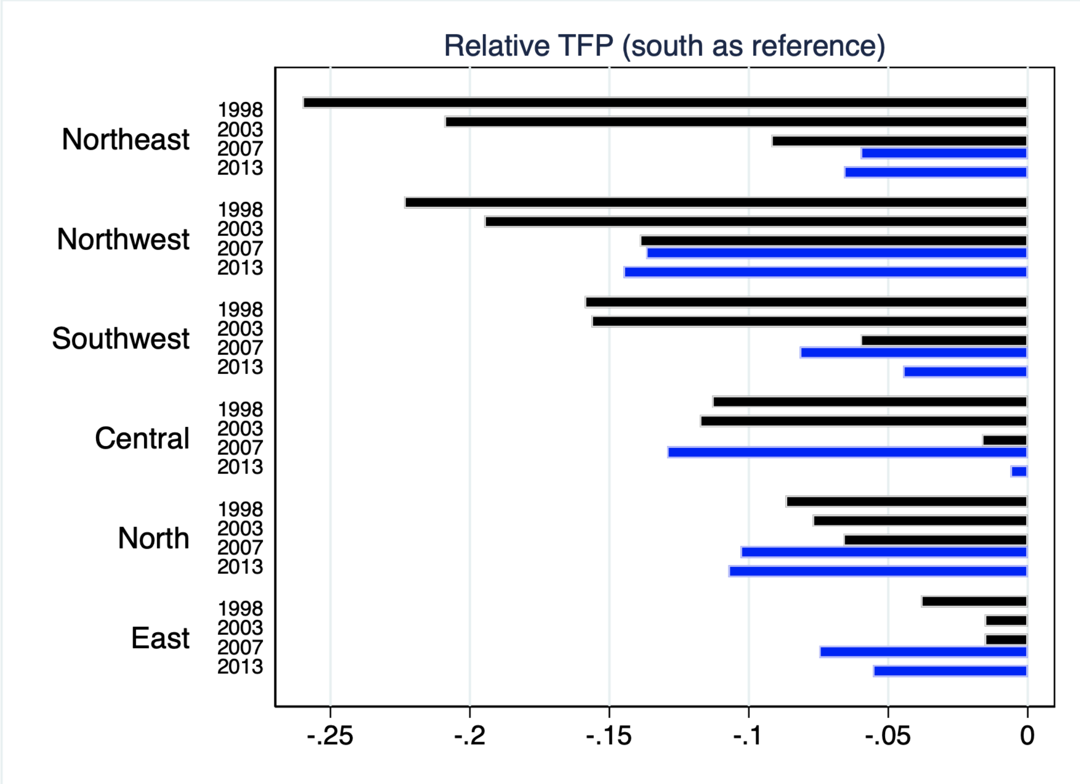


Notes: Each point represents an industry by province combination. TFP levels and growth rates are both demeaned across all provinces by industry. The graph in the lower panel is based on simulated samples with a constant weighting function.

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 (2023) 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. Their relaxation lead to more and more productive entrants. Other reforms that reduced the fixed costs of entry may have 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.

Figure 11: Evolution of productivity levels across regions (relative to South)



Notes: The relative TFP level of each region is the weighted average of the differences with the South, the reference region, of the productivity levels across industries and provinces. Estimates are based on simulated samples with a constant weighting function.

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 capture 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 only reflect the STA's sample rotation scheme.

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 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. It does not measure the TFP change at the group level, 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

$$\overline{\omega}_t - \overline{\omega}_0 = \sum_{i \in C} s_{it} \left(\omega_{it} - \overline{\omega}_0 \right) + \sum_{e \in EN} s_{et} \left(\omega_{et} - \overline{\omega}_0 \right). \tag{8}$$

The second term measures the contribution of entrants in the standard way, only entrants are defined differently. The first term captures both the contribution of continuing firms, i.e., firm-level productivity changes and between-firm changes in output shares that affect aggregate 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.

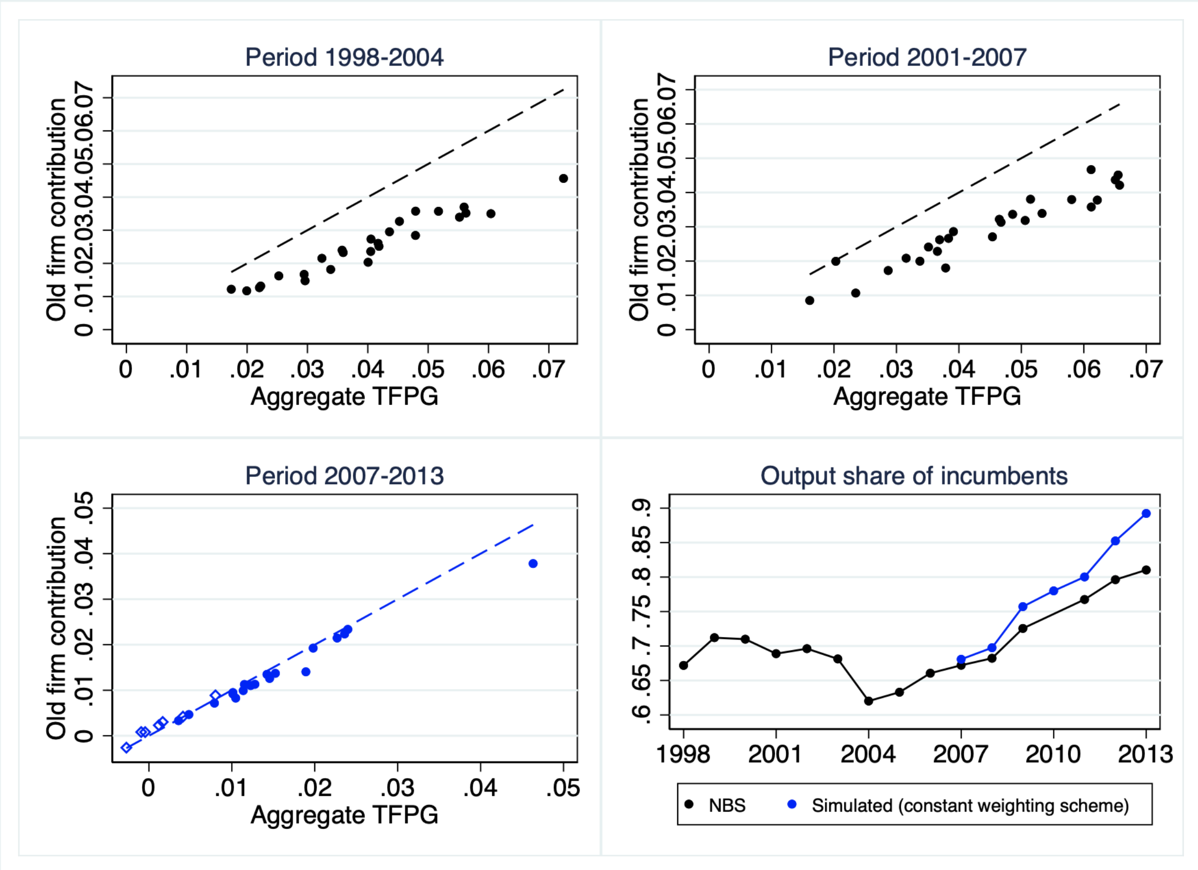
In the first three panels of Figure 12, we plot on the horizontal axis the aggregate productivity growth rate, $\overline{\omega}_t - \overline{\omega}_0$, and the contribution of incumbent and exiting firms, $\sum_{i \in C} s_{it} \left(\omega_{it} - \overline{\omega}_0 \right)$, the decomposition term from Equation 8 on the vertical axis. 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.

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 implies that productivity growth is much lower in 2007-2013. Second, the much smaller gap between the markers and the 45-degree line implies that the contribution of entrants to productivity growth is much smaller in the later period. Incumbent and exiting firms' contribution to aggregate TFP growth rises from 67% to 85% and that of entrants' falls from 33% to 15%. Note that the smaller relative contribution of entrants coincides with a decline in annual TFP growth from 4.5 percent before 2007 to only 1.4 percent afterwards.

Remarkably, there are a number of industries for which the markers for 2007-2013 period even lie above the 45-degree line.[25] 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

[25] These industries are represented by hollow diamond and labeled with 2-digit industry code.

Figure 12: Old firms' contribution to aggregate productivity growth

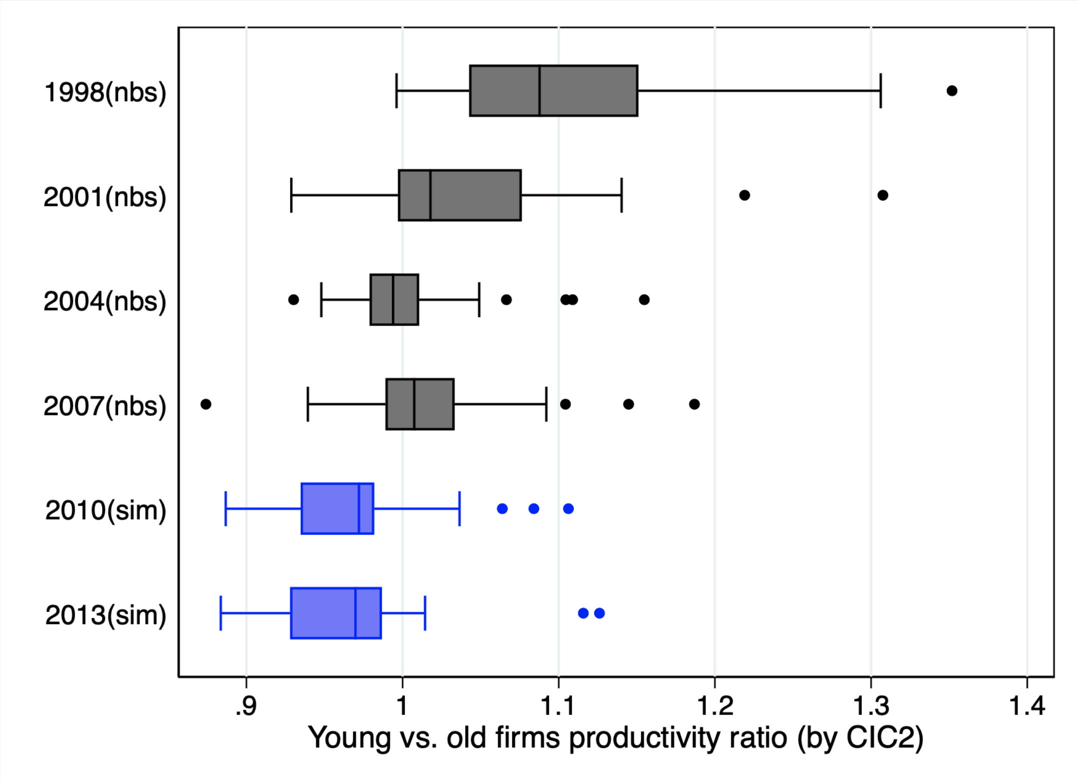


Notes: The results for 2007-2013 use samples simulated with a constant weighting function. Over the three 6-year periods, annualized TFP growth of the manufacturing sector is 4.0%, 4.2% and 1.4%, while the TFP level of continuing firms is, respectively, 4.6%, 4.5% and 1.4% higher than the initial aggregate level. Diamonds markers represent 2-digit industries where the entry margin contributes negatively to industry-level productivity growth. From left to right, these are CIC13 (food processing), CIC29 (rubber products), CIC25 (oil processing and coking), CIC34 (metal products), CIC35 (general machinery), CIC17 (textile), and CIC14 (food manufacturing).

fraction of 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 shows the remarkable increase in manufacturing output of these firms. 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 simulated samples based on the STA survey where the reported output estimates are more reliable, their share in 2013 is almost as high as 90 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 document the distribution of relative TFP of new entrants by industry for several years. New firms are defined as firms established within the last six years. Figure

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



Notes: The whisker-box summarizes the distribution of relative productivity of young firms versus incumbents across 2-digit industries. The simulated samples are based on a constant weighting function.

B.4 in the Appendix contains a similar figure for new firms established within the last three years. Until 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 of business in all but a few industries.

Table 4 contains complementary information on the size of the cohort of new entrants, with a breakdown by firm type. New entrants here are firms established within the last two years that are new to the NBS sample. Consistent with the new NBS size threshold from 2011 onward, we focus throughout on firms with reported revenue above 20 million RMB. From 2007 to 2013, the share of entrants declined from 8% of active firms to less than 5%.

The decline is especially pronounced for foreign-invested firms. In 2013, the two types of foreign-invested firms combined represented 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 firms entering annually

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

Table 4: Falling entry rates in the NBS survey

	Total	Entry Rate	Share of New Entrants (%)			
Year			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 firms at the beginning of the year multiplied by 100.

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: The table reports for each period the average number of new entrants per year as defined by their year of establishment. Light, heavy and advanced are defined at the CIC 2-digit level, and described in the Appendix. Source: Business Registry of China.

only 60 percent of the level between 2008-2014. Moreover, the entry of foreign firms in manufacturing is increasingly concentrated in a few technologically advanced 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 TFP growth to two remaining measurement issues.

First, the discussion in Section 2.2 concluded that under-reporting of revenue and over-reporting of inputs has lessened over time with reforms by the STA. This implies that our TFP growth estimate in the later period can be taken as an upper bound. However, the problem of over-reporting output and value added in the NBS data 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 sales 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 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]

[27] Across 8 manufacturing industries, the average "direct input coefficient" in China's input-output

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

	Period and firm sample used:		
	NBS 1998-2007	STA 2007-2013	STA 2007-2013
Production function estimates:		(Constant weights)	(Time-varying weights)
NBS, 1998-2007	4.4	1.4	1.3
STA, 2007-2013 (Constant)	4.5	1.5	
STA, 2007-2013 (Time-varying)	4.2		1.4

A second channel through which misreporting can influence productivity growth is the estimated output elasticities of the production technology which determine the importance of each input in our growth accounting. To verify the robustness of the TFP estimates to this issue, we calculate TFP growth for both periods, 1998-2007 and 2007-2013, with the production function parameters estimated on either period. Table 6 reports the alternative estimates of aggregate annual TFP growth and the panels in Figure B.5 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 the 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, which reduces the quality of the data and makes estimates of productivity based on these data after 2007 less credible. We leverage alternative firm-level data collected by China's State Tax Administration in which 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 and broad-based decline in TFP growth since 2007 that cuts across all industries, regions, and ownership. A 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 eliminated the productivity gap in manufacturing with advanced countries, an important source of productivity gains for

table rose from 0.72 in 1997 to 0.77 in 2007 and increased further to 0.79 in 2012.

a developing country. Although the pace of convergence in industry has been faster than in services, recent research suggests a sizeable productivity gap 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 flows. Productivity growth and business dynamism declined in advanced countries (Fernald 2015, Decker et al., 2020). For China, sharply falling productivity growth may reflect demand shocks and lower rates of capacity utilization as well as smaller knowledge spillovers. Finally, 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 with legal entities, the STA survey also includes non-legal entities with independent accounting systems.

The sectoral coverage of the NBS data for 2008-2013 is the same as the 1998-2007 data. It includes the sectors of mining, manufacturing, and utilities. In a marked difference, the STA data's coverage is much broader, spanning almost all sectors of the economy (e.g., agriculture, mining, manufacturing, utilities, construction, and services). In our paper, we focus on the manufacturing sector. Manufacturing firms accounted for 43.2 percent and 36.2 percent of all firms in 2007 and 2013, respectively.

Compared with the NBS data, the STA data provide much richer information about the firms. The number of variables varies from year to year, around 350 to 450. In addition to firms' basic information and financial information, which are typically included in the NBS data, the firms in the STA data also report detailed operation information related to 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 use the Chinese Industry Classification (CIC), a part of the National Standards of the People's Republic of China. Originally introduced in 1984, the CIC has undergone several revisions. To accommodate the dynamic industrial growth, the government consolidated some declining industries and introduced new codes for emerging industries. During our sample period between 1998 and 2013, the CIC evolved from the 1994 revision to the 2002 and 2011 revisions. For clarity and consistency, we developed a concordance table of these three revisions by grouping those industries that were split in other revisions. In total, we have 418 manufacturing industries in our new classification.

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. This producer price index saw an increase in 2008, 2010, 2011, and 2012, while observing a decline in 2009 and 2013.

To calculate real value added, we also need input deflators. Following Brandt et al. (2012, 2014), we use the aforementioned output deflators and the 2012 National Input-Output Table. We also calculated alternative input deflators using both 2007 and 2012 input-output tables. Since the input-output tables usually change very slowly over time, the difference between these two sets of input deflators is negligible.

A.4 Ownership

The NBS data include firm ownership indicators in addition to a breakdown of registered capital by ownership. Both are useful for identifying ownership, especially those firms that are under state control. For the STA data, we only have the ownership indicators. A literal definition of state ownership usually includes ownership codes 110, 141, 143, and 151. For earlier years, the number of firms thus defined as state-owned in industry lines up reasonably well with numbers reported in the Statistical Yearbook. The gap widens over time, however, because these four categories do not capture other ownership types under state control, most notably, shareholding companies (160). In principle, information on registered capital can be used to identify these firms, however, we do not have this information for the STA sample. We choose to use a broader definition of SOEs that includes shareholding companies, and the resulting above-scale SOE counts are very close to the numbers reported in China's Statistical Yearbooks.

A.5 Real capital stock

Based on the original value of fixed assets, we follow Brandt et al. (2012, 2014) and use the perpetual inventory method to calculate the real capital stock in the STA sample. The process follows three steps. First, calculate the nominal capital stock in the firm's founding year. We use the 1993 annual enterprise survey and the NBS data after 1998 to calculate the average growth rate of nominal capital stock at the province-two-digit industry level between the firm's founding year and the first year that the firm appears in our data. Assuming that the firm-specific growth rate of nominal capital stock is equal to the provincial industry average, we can calculate the nominal capital stock in the firm's founding year. Second, combining the investment deflators and 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 of data appearance. Third, we can further calculate the real capital stock of the following years since we observe the value of firm investment in our data after 2007.

A.6 Merging the two samples

The NBS data provide firm names for all years. However, the STA data report firm name only for 2007-2011. In terms of firm IDs, the NBS and STA data appear to have their own coding system at first glance. The NBS data have a 9-digit firm ID, while the STA firm ID has 15 digits. However, closer examination shows that the first 6 digits of the STA data are geographic codes, while the last 9 digits correspond to the NBS firm ID. As a result, we merge the NBS and STA data using both firm ID and name in these two samples. The detailed results of the merging are reported in Table 1.

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 sharp decrease in the number of firms in the NBS sample with sales below 5 million RMB after 2010 reflects the increase in the minimum size threshold.

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

	GVIO (trillion RMB)				Value added (trillion RMB)				VA/GDP Industry	VA/GVIO (%)			
	NBS	STA(1)	STA(2)	STA(3)	NBS	STA(1)	STA(2)	STA(3)	(%)	NBS	STA(1)	STA(2)	STA(3)
1998	5,570				1,380				57.2	24.8			
1999	5,970				1,530				60.2	25.6			
2000	7,050				1,800				63.6	25.5			
2001	7,880				2,020				64.2	25.6			
2002	9,300				2,420				69.8	26.0			
2003	12,200				3,170				76.6	26.0			
2004	16,800				4,290				87.8	25.5			
2005	20,900				5,390				93.7	25.8			
2006	26,400				6,850				100.0	25.9			
2007	34,100	16,000	31,000	27,900	8,900	3,140	6,370	5,610	106.1	26.1	19.6	20.5	20.1
2008	41,300	17,500	37,600	36,400		3,370	7,210	7,290			19.3	19.2	20.0
2009	43,000	20,600	37,500	33,500		3,970	7,570	6,600			19.3	20.2	19.7
2010		29,200	43,700	38,500		5,590	8,560	7,200			19.1	19.6	18.7
2011	69,100	35,500	52,500	49,900		5,850	9,880	9,210			16.5	18.8	18.5
2012	73,400	36,100	56,700	54,600		5,760	10,300	9,810			16.0	18.2	18.0
2013	85,800	35,800	59,900	56,800		6,010	11,200	10,400			16.8	18.7	18.3

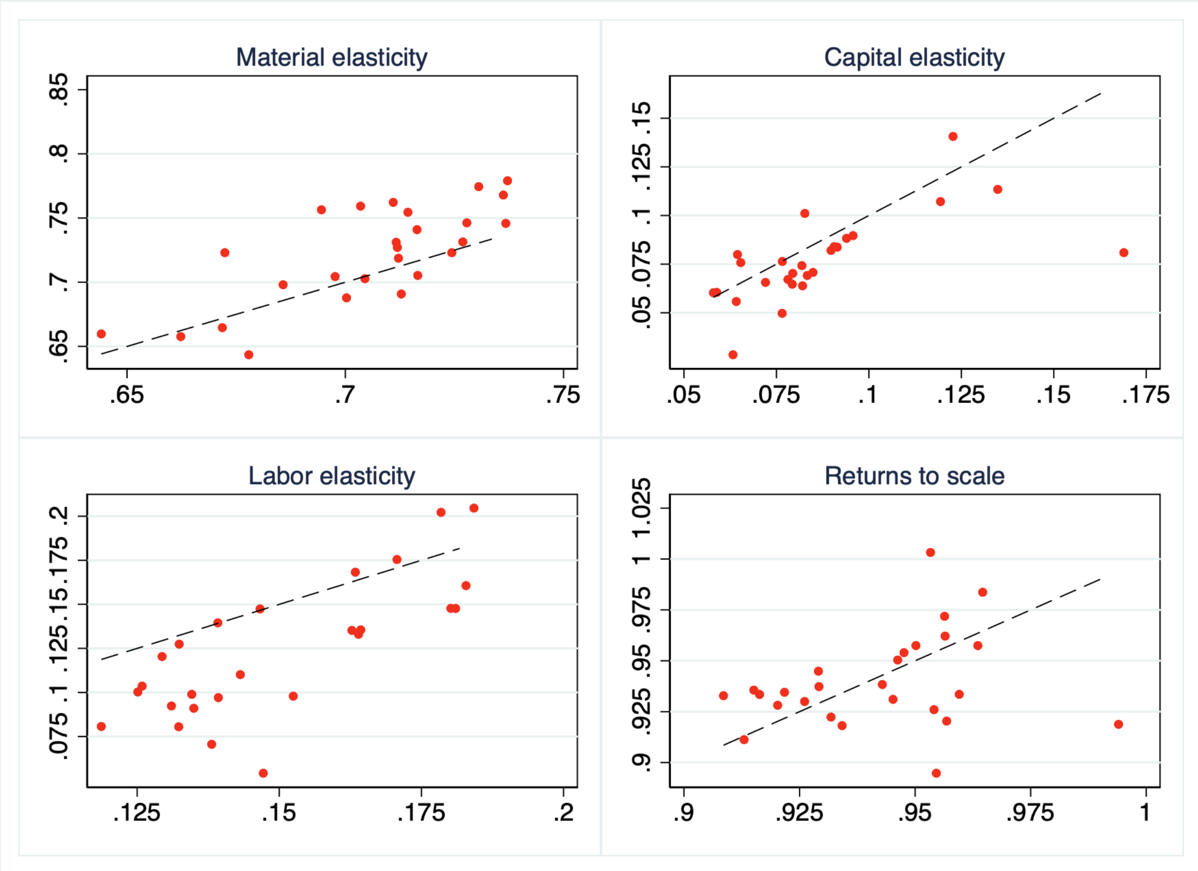
Notes: GVIO is the gross value of industrial output. STA(1) is the unweighted STA sample; STA(2) is the constant-weight STA sample; and STA(3) is the time-varying-weight STA sample. VA/GDP Industry is the ratio of value added in industry in the NBS sample to GDP in industry in the national income accounts.

Appendix B. Additional results

Table B.1: Annualized TFP growth rates by industry

CIC industries	1998-2007	2007-2013	
		Constant weights	Time-varying weights
13	2.6	-0.3	-0.1
14	4.5	0.8	0.1
15	5.2	1.9	0.8
17	3.3	0.4	0.6
18	3.2	0.7	1.1
19	2.6	1.5	1.0
20	3.5	0.5	0.1
21	2.7	1.3	1.3
22	4.1	1.1	2.1
23	4.0	0.8	1.8
24	2.8	1.0	1.2
25	3.1	0.2	-1.5
26	5.2	1.4	1.7
27	5.6	2.4	2.7
29	3.7	0.5	-0.6
30	2.7	1.1	1.0
31	5.6	1.0	1.6
32	5.5	2.2	2.3
33	3.1	1.3	1.0
34	3.9	0.1	0.2
35	5.7	-0.1	0.6
36	5.5	0.6	0.3
37	6.3	3.3	1.8
39	4.0	1.4	1.5
40	4.2	4.6	3.9
41	4.3	2.2	2.0
All of manufacturing	4.4	1.5	1.4

Figure B.1: Output elasticities estimated on two periods (time-varying weighting function)



Notes: Three panels show the output elasticities with respect to each of the three inputs, estimated using a non-parametric production function over the 2007-2013 period on the simulated samples (with 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 industry. The dashed line is the 45-degree line.

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

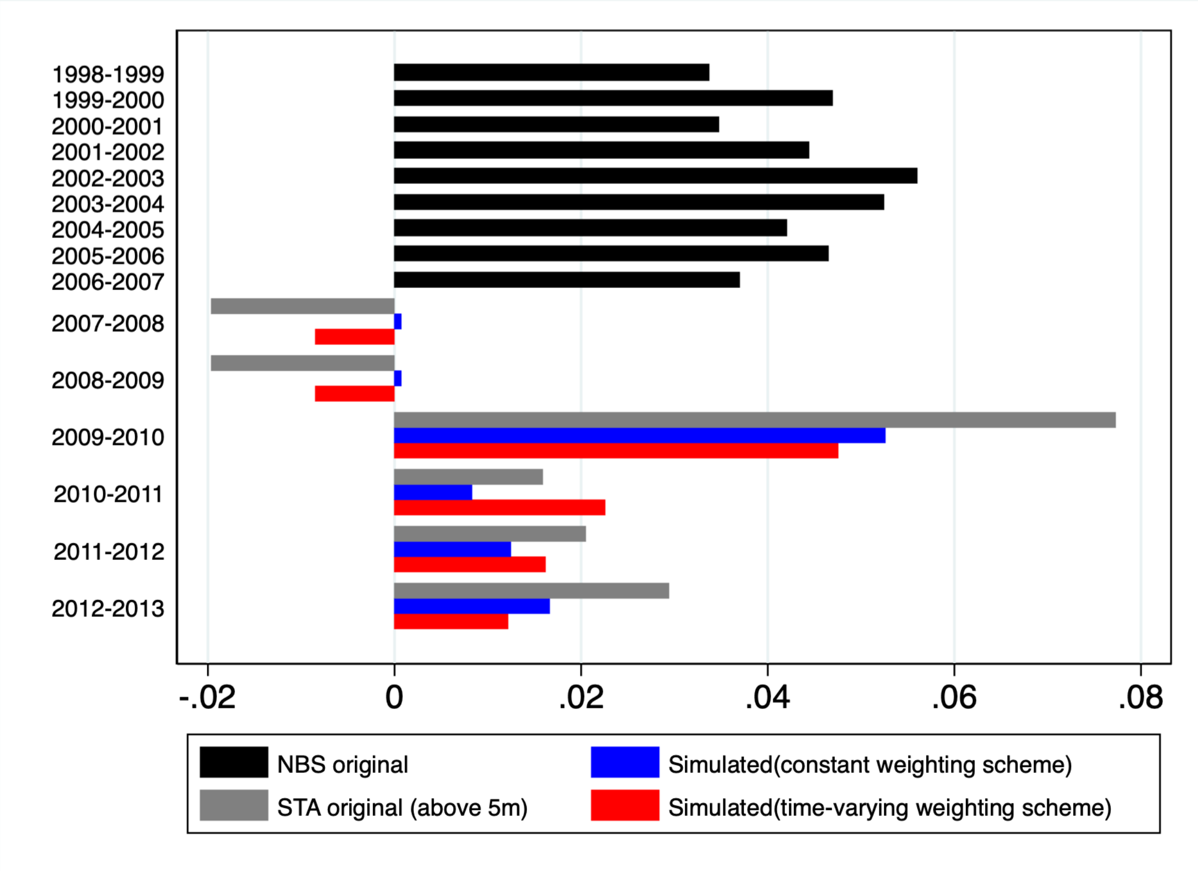
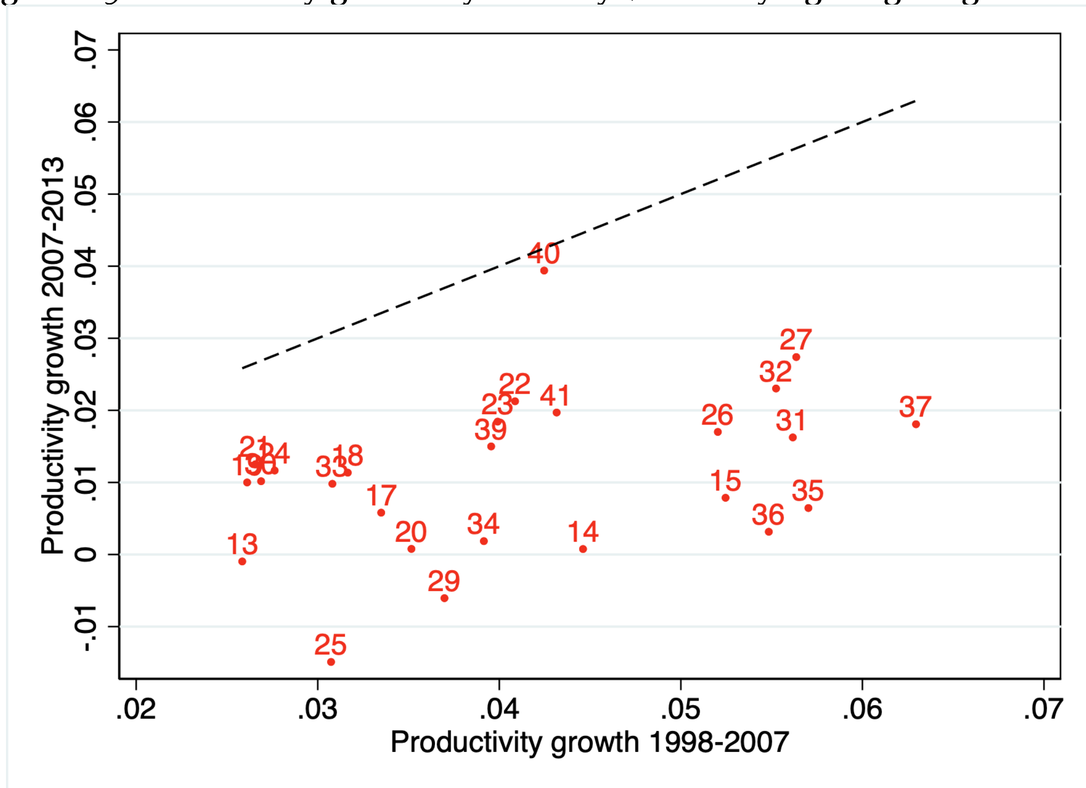
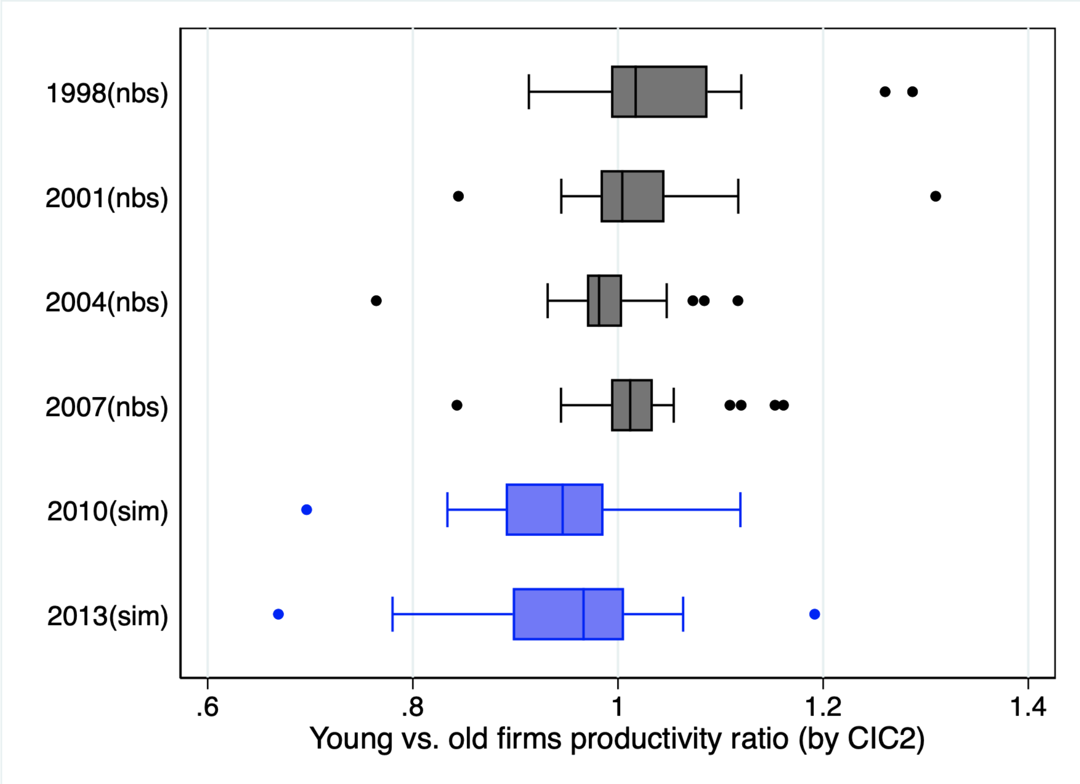


Figure B.3: Productivity growth by industry (time-varying weighting function)



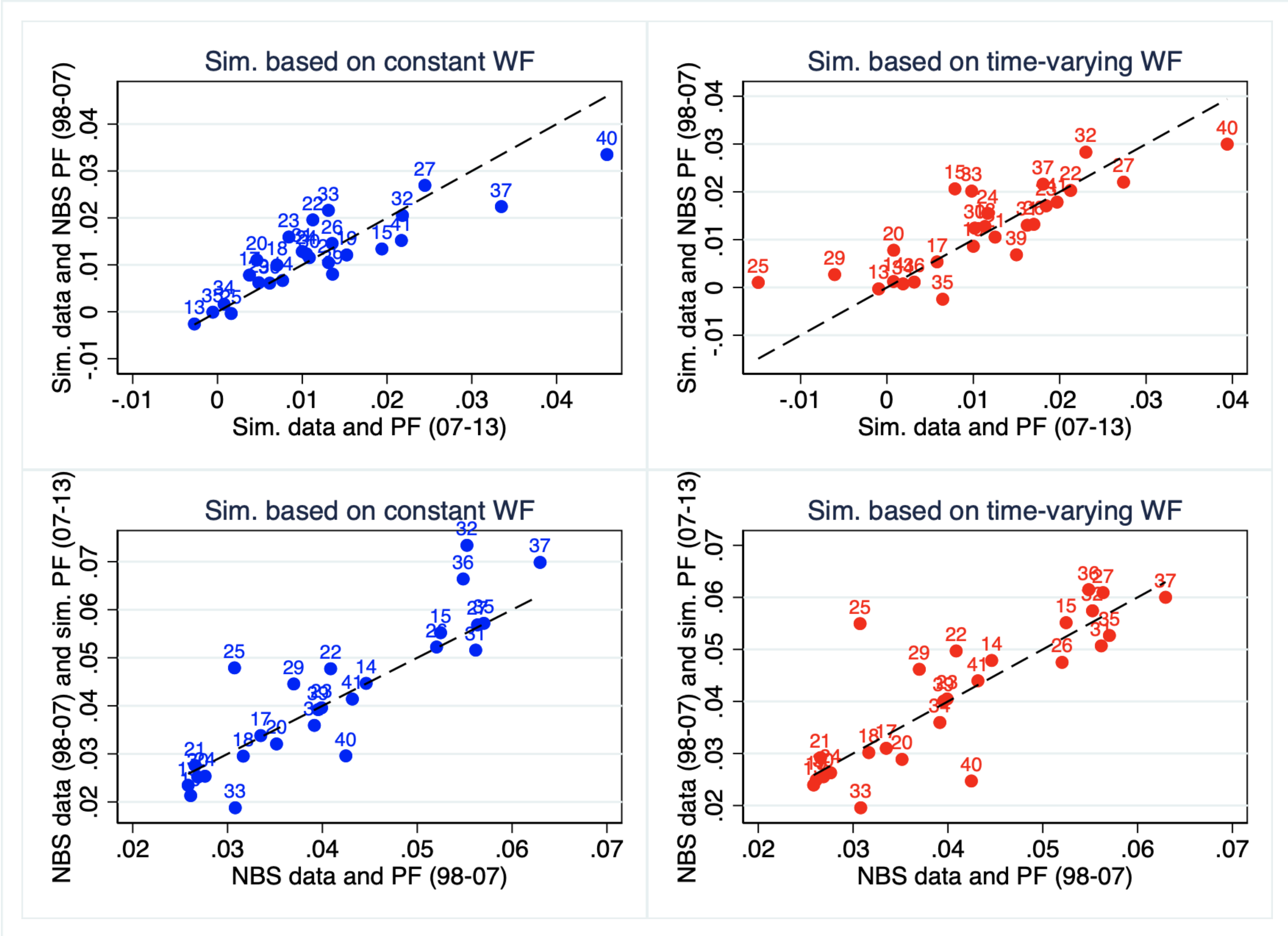
Notes: The results for 2007-2013 use samples simulated with a time-varying weighting function. The dashed line is the 45-degree line.

Figure B.4: Falling relative productivity of young firms ($\leq$ 3 years)



Notes: The whisker-box summarizes the distribution of relative productivity ratio across 2-digit CIC industries. The simulated samples are based on constant weighting functions.

Figure B.5: TFP growth by industry based on different production function estimates



Notes: Graphs on the left use a constant weighting function and those on the right a time-varying weighting function. Graphs at the top show TFP growth rates on 2007-2013 calculated using 2 sets of production function estimates and those at the bottom TFP growth on 1998-2007 also calculated two ways.