Technology intensity and ownership in the Chinese manufacturing industry: A labor productivity decomposition approach

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Abstract

China's manufacturing industry has registered phenomenal development in the past 40 years, which has become the most remarkable aspect of China's economic miracle. Yet researchers give different explanations to China's rapid growth. In this paper, we employ a tripartite decomposition to study the driving force of productivity growth in China's manufacturing industry during 1998–2007. A detailed firm-level dataset enables us to construct accurate measures of inputs and output at the sectoral level. We highlight the importance of technology heterogeneity in reconciling different decomposition results and making interpretations. Our results show strong labor productivity growth in China's manufacturing industry. When we control technology heterogeneity, we find that most of the productivity growth (125.60%) was driven by capital deepening (give % here), technology progress contributed another 62.47%, and a small fraction (11.23%) was due to efficiency improvement. China's manufacturing industry exhibits strong productivity convergence. We demonstrate that this convergence was driven by technology change and capital deepening effects, but not efficiency change. These results suggest that China's overall industry development benefited from market mechanism in resource allocation and technology diffusion. We point out that China's industry can still benefit from capital accumulation in the near future but long-term productivity growth must be based on technology progress.

Keywords: technology gap; technical efficiency; manufacturing industry; China; metafrontier.

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1 Introduction

China has achieved phenomenal growth in its industrial sector since the 1980s. From 1980 to 2017, total industrial value added increased from 603.9 billion to 26.7 trillion RMB, or 43.2 times.[1] Nowadays, China accounts for 20.9% of the world's industrial value added, and China is the top producer of 220 industrial products.[2] The strong industry explains why China is often called *the factory of the world*.

Against the backdrop of China's great leap in industrial development was vibrant productivity growth. From 1980 to 2017, the labor productivity in China's industry increased 22 times and reached $21,567 per worker, which was far greater than that of middle-income countries ($16,905 per worker) but slightly lower than that of upper-middle-income countries ($23,427 per worker).[3] Although a huge productivity gap still exists between China and developed economies, data show that China is catching up rapidly.[4] Clearly, labor productivity growth is the key to understand China's industrial development.

Empirical studies on China often address two research questions. First, what are the driving forces of China's productivity growth? Second, has there been convergence or divergence during China's high-speed growth? Depending on the methodology being used and the subject of study. researchers give different answers to these questions. Growth decomposition has been widely applied to investigate China's regional economic growth, but not China's industry (Badunenko & Tochkov, 2010; Henderson, Tochkov, & Badunenko, 2007; Unel & Zebregs, 2009).[5] These studies usually identify resource accumulation as the predominant source of labor productivity growth. They also report divergence among Chinese regions. Recently, there has been a burgeoning volume of studies on China's manufacturing industry. Regressional analyses often show a greater role of total factor productivity (TFP) than factor accumulation in explaining industrial output growth (Brandt, Van Biesebroeck, & Zhang, 2012; S. Chen, Jefferson, & Zhang, 2011) remove S.. These studies also show convergence of TFP among ownership types or across regions (Berkowitz, Ma, & Nishioka, 2017; Deng & Jefferson, 2011; Jefferson,

[1] Source: National Bureau of Statistics. Industrial value added is in 2015 constant price.

[2] Source: World Bank Open Data and http://finance.people.com.cn/n1/2019/0920/c1004-31365026.html.

[3] Source: National Bureau of Statistics and World Bank Open Data.

[4] Over the 1997–2017 period, the growth rate of labor productivity was 8.1% per annum in China, compared with 1.9% in the European Union, 2.2% in Japan, and 1.7% in the United States. Data source: World Bank Open Data and author's own calculations.

[5] Walheer (2019b) is an exception, but this study is restricted to a limited number of industrial parks.

Rawski, & Zhang, 2008; Lemoine, Poncet, & Ünal, 2015). Given the differences in research method, a growth decomposition analysis for China's manufacturing industry is a missing link in this literature.

In this article, we investigate the driving forces of China's industrial labor productivity using a rich firm-level dataset for 1998–2007. For the first time, the dataset allows us to develop accurate measures for inputs and output for detailed industrial sectors. Methodologically, we follow Kumar and Russell (2002) and decompose labor productivity growth into efficiency change, technology change, and input change (capital deepening) effects. We employ data envelopment analysis (DEA) to estimate the potential outputs of a given technology. DEA, first presented by Charnes, Cooper, and Rhodes (1978) and Banker, Charnes, and Cooper (1984), is an attractive modeling technique because it does not assume *a priori* any functional form for the technology, as parametric methods do. These assumptions are usually restrictive and not always innocuous.[6] As another desirable feature, DEA allows us to easily decompose TFP growth into efficiency change and technology change (Bos, Economidou, & Koetter, 2010). Such a treatment is critical for the various growth decompositions seen in the literature, including Färe, Grosskopf, Norris, and Zhang (1994), Kumar and Russell (2002), Henderson and Russell (2005), Badunenko and Romero-Ávila (2013), Walheer (2018c), and Walheer (2019b).

A distinguishing feature of our study is to incorporate technology heterogeneity into the analysis. Theories postulate that economic units choose technologies that match their factor combinations, resulting in technology clubs (Atkinson & Stiglitz, 1969; Basu & Weil, 1998). Empirically, it has been shown that technology heterogeneity exists across sectors (Bos, Economidou, & Koetter, 2010; Molinos-Senante, Maziotis, & Sala-Garrido, 2017; Walheer, 2016b, 2018a, 2018b, 2019c), regions (Bos, Economidou, Koetter, & Kolari, 2010; Filippetti & Peyrache, 2015; Walheer, 2016b, 2018c, 2019a), and ownership types (Badunenko & Kumbhakar, 2017; Elyasiani & Rezvanian, 2002). In the Chinese context, S. Chen et al. (2011) remove S. and Ding, Guariglia, and Harris (2016) highlight sectoral difference in China's industry, whereas M. Chen and Guariglia (2013) remove M. and Guariglia, Liu, and Song (2011) emphasize differences across ownership types.

Based on these considerations, we employ the concept of metafrontier developed by Battese and Rao (2002) and model two levels of heterogeneity in technol-

[6]See, for example, discussions in Hsieh and Klenow (2009) about the impact of the Cobb-Douglas assumption on their results.

ogy: that between technology groups and that between ownership types.[7] Such a treatment is similar to those of He and Walheer (in press) and Walheer and He (in press). In the growth decomposition, the introduction of the metafrontier implies a further decomposition of each component into a group effect and a heterogeneity component. The application of metafrontier techniques in growth decomposition has received increasing attention in recent years. Examples include Fei and Lin (2016), Filippetti and Peyrache (2015), Molinos-Senante et al. (2017), Walheer (2019a), and N. Zhang and Choi (2013) remove N.. However, none of these applications considers more than one level of heterogeneity. Thus, we also contribute to the literature of growth decomposition.

Our analyses reveal strong labor productivity growth in China's manufacturing industry during 1998–2007. When we control for technology heterogeneity, we find that most of the productivity growth (125.60%) was explained by capital deepening give percentage, followed by technology progress (62.47%). The contribution of efficiency change was small (11.23%) because the room for efficiency improvement was already small in 1998. We find strong convergence of labor productivity across ownership types and among the medium- and high-tech groups. We show that convergence was driven by technology change and capital deepening. We demonstrate the importance of heterogeneity components in explaining variations in the decomposition when using different reference technologies. We then link our study to the recent literature on China's productivity growth and synthesize these findings. Finally, we discuss policy implications of our results.

The rest of this article is organized as follows. Section 2 introduces the methodology. In Section 3, we present our empirical findings, make interpretations, and discuss their implications. Finally, Section 4 concludes the study.

2 Methodology

Our aim is to suggest a new decomposition of labor productivity growth when technology heterogeneity between entities (e.g., firms, regions, sectors) is taken into consideration. We start by defining the groups and the technologies and introduce our concepts of technical efficiency and technology gap. Next, we explain how to decompose labor productivity into several parts when entities belong to different technologies. Finally, we show how our different indicators can be computed by

[7] The concept of metafrontier is based on the notion of meta-production set by Hayami and Ruttan (1970). We refer the reader to Battese, Rao, and O'Donnell (2004) and O'Donnell, Rao, and Battese (2008) for more details of the metafrontier methodology.

means of linear programs.

2.1 Groups and technologies

We assume that we observe decision making units (DMUs) from I groups where each group is composed of K_i types, for $i = 1, \dots, I$ during T time periods.[8] Also, we consider that DMUs use P production factors, captured by $\mathbf{x}^t \in \mathbb{R}_+^P$, to produce one output, captured by $y^t \in \mathbb{R}_+$, at time $t = 1, \dots, T$.

We define the technology in terms of output requirement sets. Given our setting, we distinguish between three levels: each type in every group; each group; and when considering all groups. The output requirement sets are given as follows:

$$P_{ik}^t(\mathbf{x}) = \{y \mid \mathbf{x} \text{ can produce } y \text{ in type } k \text{ of group } i \text{ at time } t\}. \tag{1}$$
$$P_i^t(\mathbf{x}) = \{y \mid \mathbf{x} \text{ can produce } y \text{ in group } i \text{ at time } t\} \tag{2}$$
$$P^t(\mathbf{x}) = \{y \mid \mathbf{x} \text{ can produce } y \text{ at time } t\} \tag{3}$$

We label $P_{ik}^t(\mathbf{x})$ the group-type output requirement set, $P_i^t(\mathbf{x})$ the group-specific output requirement set, and $P^t(\mathbf{x})$ the overall output requirement set. These sets contain the output quantities that can be produced by the inputs $\mathbf{x}$ at time t at different levels. They are related as follows:

$$P_i^t(\mathbf{x}) = P_{i1}^t(\mathbf{x}) \cup \cdots \cup P_{iK_i}^t(\mathbf{x}), \text{ for } i = 1, \dots, I, \tag{4}$$
$$P^t(\mathbf{x}) = P_1^t(\mathbf{x}) \cup \cdots \cup P_I^t(\mathbf{x}). \tag{5}$$

A first implication is the following: $P_{ik}^t(\mathbf{x}) \subseteq P_i^t(\mathbf{x}) \subseteq P^t(\mathbf{x})$, for all i, k, and t. Next, $P_i^t(\mathbf{x})$ can be viewed as the envelopment of $P_{ik}^t(\mathbf{x})$, and $P^t(\mathbf{x})$ as the envelopment of $P_i^t(\mathbf{x})$. At this point, we remark that the envelopment is, generally, non-convex (give references; my paper in EJOR + there are 2 others papers in EJOR (Kristiaan Kerstens, Christopher O'Donnell, Ignace Van de Woestyne AND Mohsen Afsharian, Victor V. Podinovski and 1 paper in JORS about hotels.). This will directly impact the computation (see Section 2.5). This also implies the following:

$$P_i^t(\mathbf{x}) = \left\{P_{11}^t(\mathbf{x}) \cup \cdots \cup P_{1K_1}^t(\mathbf{x})\right\} \cup \cdots \cup \left\{P_{I1}^t(\mathbf{x}) \cup \cdots \cup P_{IK_I}^t(\mathbf{x})\right\}. \tag{6}$$

[8]In our empirical study, a DMU comprises all firms of a certain ownership type within an industrial sector. These DMUs are first categorized into three technology groups, and then divided into three ownership types.

Thus, $P^t(\mathbf{x})$ represents the meta technology set, i.e., when considering all groups (and thus all types) at time t.

2.2 Inefficiency and technology gap

We define inefficiency as the ability of DMUs to increase their output when keeping their inputs constant. To formally define (in)efficiency, we introduce the concept of potential outputs. Intuitively, potential outputs refer to the maximal output expansion with respect to the frontier of the chosen output requirement set. Given our technology heterogeneity context, we have three different potential outputs:

$$y_{ik}^t(\mathbf{x}) = \max\left\{y \mid y \in P_{ik}^t(\mathbf{x})\right\}. \tag{7}$$

$$y_i^t(\mathbf{x}) = \max\left\{y \mid y \in P_i^t(\mathbf{x})\right\}. \tag{8}$$

$$y^t(\mathbf{x}) = \max\left\{y \mid y \in P^t(\mathbf{x})\right\}. \tag{9}$$

Intuitively, actual output cannot exceed the potential values, implying that $y_{ik}^t\left(\mathbf{x}^t\right) \geq y^t$, $y_i^t\left(\mathbf{x}^t\right) \geq y^t$, and $y^t\left(\mathbf{x}^t\right) \geq y^t$ for any DMU of type k in group i whose input-output mix is $(\mathbf{x}^t, y^t)$ at time t. If they coincide, it reveals that the output is at its optimal value (with respect to the reference technology). Moreover, we have, by construction, that $y^t(\mathbf{x}) \geq y_i^t(\mathbf{x}) \geq y_{ik}^t(\mathbf{x})$ for any $\mathbf{x}$. In words, potential output with respect to the group-type technology cannot exceed the potential output with respect to the group-specific technology, which cannot exceed the potential output with respect to the overall technology. Intuitively, this reflects that the group-type technology sets are included in the group-specific technology sets, which are themselves included in the overall technology set.

A well-established indicator to capture the extent to which output can be raised is the Debreu–Farrell give the reference ? that is include the year here technical efficiency ratio. For any DMU of type k in group i whose input-output mix is $(\mathbf{x}^t, y^t)$better to define for $(\mathbf{x}, y)$ at time t, we define:

$$e_{ik}^t\left(\mathbf{x}^t, y^t\right) = \frac{y^t}{y_{ik}^t\left(\mathbf{x}^t\right)}. \tag{10}$$

$$e_i^t\left(\mathbf{x}^t, y^t\right) = \frac{y^t}{y_i^t\left(\mathbf{x}^t\right)}. \tag{11}$$

$$e^t\left(\mathbf{x}^t, y^t\right) = \frac{y^t}{y^t\left(\mathbf{x}^t\right)}. \tag{12}$$

Depending on the reference technology, these three ratios provide three different levels of technical efficiency: $e_{ik}^t\left(\mathbf{x}^t, y^t\right)$ is the group-type technical efficiency, which measures the gap between the actual output y^t and the potential output of the technology that is available to type k in group i; $e_i^t\left(\mathbf{x}^t, y^t\right)$ is the group-specific technical efficiency, which is relative to the potential output of the group-specific technology; and $e^t\left(\mathbf{x}^t, y^t\right)$ is the overall technical efficiency, which is with reference to the potential output of the overall technology. As discussed previously, the actual output cannot exceed potential outputs, so the technical efficiency ratios are no greater than unity. When the ratio equals one, the output is at its maximal value with respect to the reference technology set. When the ratio is smaller than one, output can, in principle, be increased without increasing the production factors. Moreover, given the ranking between the potential outputs discussed previously, we also have $e_{ik}^t\left(\mathbf{x}^t, y^t\right) \geq e_i^t\left(\mathbf{x}^t, y^t\right) \geq e^t\left(\mathbf{x}^t, y^t\right)$.

Next, we construct two measurements for the technology difference between the hierarchy levels. For any input mix $\mathbf{x}$, we define:

$$g_{ik}^t(\mathbf{x}) = \frac{y_{ik}^t(\mathbf{x})}{y_i^t(\mathbf{x})}. \tag{13}$$

$$g_i^t(\mathbf{x}) = \frac{y_i^t(\mathbf{x})}{y^t(\mathbf{x})}. \tag{14}$$

$g_{ik}^t(\mathbf{x})$ is the group-type technology gap and $g_i^t(\mathbf{x})$ is the group-specific technology gap at time t. That is, $g_{ik}^t(\mathbf{x})$ captures the technology gap between the technology that is specific to type k and the technology that is available to group i, whereas $g_i^t(\mathbf{x})$ captures the technology gap between the technology that is specific to group i and the overall technology. Both ratios are smaller than one, which can be seen from the relationship between the potential outputs, i.e., $y^t(\mathbf{x}) \geq y_i^t(\mathbf{x}) \geq y_{ik}^t(\mathbf{x})$. A value of one reveals no technology gap, while a smaller value implies more gaps.

Using our two gap indicators, we can obtain an useful decomposition of potential output with respect to the group-type technology as follows:

$$y_{ik}^t(\mathbf{x}) = g_{ik}^t(\mathbf{x}) \times g_i^t(\mathbf{x}) \times y^t(\mathbf{x}). \tag{15}$$

Intuitively, there are two gaps between the potential output of the group-type technology $y_{ik}^t(\mathbf{x})$ and that of the overall technology $y^t(\mathbf{x})$: the group-type and the group-specific technology gaps. This is a direct implication of the three hierarchy levels.

Finally, we remark that the previous equation can be rewritten in terms of efficiency measurements. It suffices to evaluate (15) at $\mathbf{x}^t$, then divide both sides by the actual output y^t: better to define for $(\mathbf{x}, y)$

$$e^t\left(\mathbf{x}^t, y^t\right) = g^t_{ik}\left(\mathbf{x}^t\right) \times g^t_i\left(\mathbf{x}^t\right) \times e^t_{ik}\left(\mathbf{x}^t, y^t\right). \tag{16}$$

That is, for any observed DMU, the overall technical efficiency is generally lower than the group-type technical efficiency, because of the two technology gaps between the hierarchy levels.

2.3 Productivity growth decomposition

Kumar and Russell (2002) suggest a useful decomposition for productivity growth that assumes a unified technology. To start with, suppose that the input-output mix of a DMU is $\left(\mathbf{x}^b, y^b\right)$ at time b and $(\mathbf{x}^c, y^c)$ at time c. The ratio of the actual outputs can be expressed as the product of two ratios: that of technical efficiency ratios and that of potential outputs. That is, we have:[9]

$$\frac{y^c}{y^b} = \frac{e^c\left(\mathbf{x}^c, y^c\right)}{e^b\left(\mathbf{x}^b, y^b\right)} \frac{y^c\left(\mathbf{x}^c\right)}{y^b\left(\mathbf{x}^b\right)}. \tag{17}$$

The next step is to introduce the counterfactual potential output $y^c\left(\mathbf{x}^b\right)$, which is the maximum output for the input mix $\mathbf{x}^b$ given the technology of time c. Multiplying the right hand side of (17) by $\frac{y^c\left(\mathbf{x}^b\right)}{y^c\left(\mathbf{x}^b\right)}$, we get

$$\begin{aligned}\frac{y^c}{y^b} =& \frac{e^c\left(\mathbf{x}^c, y^c\right)}{e^b\left(\mathbf{x}^b, y^b\right)} \frac{y^c\left(\mathbf{x}^b\right)}{y^b\left(\mathbf{x}^b\right)} \frac{y^c\left(\mathbf{x}^c\right)}{y^c\left(\mathbf{x}^b\right)} \\ =& EFF \times TECH^b \times KACC^c.\end{aligned} \tag{18}$$

Of the three terms on the right hand side, EFF is the efficiency change when the DMU changes its input-output mix from $\left(\mathbf{x}^b, y^b\right)$ to $(\mathbf{x}^c, y^c)$. $TECH^b$ measures the extent to which the production frontier shifts outward or inward when evaluated at $\mathbf{x}^b$. It captures technology change: $TECH^b > 1$ means technology progression and $TECH^b < 1$ means technology regression. $KACC^c$ measures the change of the potential output due to the change of the input mix if the technology is fixed at time c. If $\mathbf{x}$ is capital per worker and y is output per worker, as in our case, $KACC^c$ captures the effect of capital deepening. Obviously, both $TECH^b$ and $KACC^c$ depend on the chosen reference counterfactual $y^c\left(\mathbf{x}^b\right)$. If we use the other

[9] The subscripts i and k disappear because we assume a unified technology for the moment.

counterfactual $y^b(\mathbf{x}^c)$, the decomposition becomes

$$\begin{aligned}\frac{y^c}{y^b} =& \frac{e^c(\mathbf{x}^c, y^c)}{e^b(\mathbf{x}^b, y^b)} \frac{y^c(\mathbf{x}^c)}{y^b(\mathbf{x}^c)} \frac{y^b(\mathbf{x}_n^c)}{y^b(\mathbf{x}^b)} \\ =& EFF \times TECH^c \times KACC^b,\end{aligned} \tag{18$'$}$$

where $TECH^c$ is the technology change effect evaluated at $\mathbf{x}^c$ and $KACC^b$ is the input change effect if the technology is fixed at time b.

To avoid arbitrary selection of the counterfactual, Kumar and Russell (2002) adopt the "Fisher ideal index," which is the geometric mean of (18) and (18′). That is,

$$\begin{aligned}\frac{y^c}{y^b} &= EFF \times \sqrt{TECH^b \times TECH^c} \times \sqrt{KACC^b \times KACC^c} \\ &= EFF \times TECH \times KACC.\end{aligned} \tag{19}$$

2.4 Heterogeneity components

In light of the technology heterogeneity between groups and types, the conventional growth decomposition (19) is incomplete. In general, the efficiency change, or technology change, or input change effect will be different when they are evaluated using the group-type concepts. The discrepancy arises because the technology gaps in (15) and (16) will also change following the change of the production sets and the change of the input-output mix. Consequently, each of these effects can be further decomposed into a group-type counterpart and two heterogeneity components that capture the change of technology gaps (Filippetti & Peyrache, 2015; Walheer, 2019a).

Suppose we observe a DMU of type k in group i. Let's denote its input-output mix by $(\mathbf{x}^t, y^t)$, where $t \in \{b, c\}$. Using (16), we can decompose EFF in (18) as follows:

$$\begin{aligned}EFF &= \frac{e_{ik}^c(\mathbf{x}^c, y^c)}{e_{ik}^b(\mathbf{x}^b, y^b)} \frac{g_{ik}^c(\mathbf{x}^c)}{g_{ik}^b(\mathbf{x}^b)} \frac{g_i^c(\mathbf{x}^c)}{g_i^b(\mathbf{x}^b)} \\ &= EFF_{ik} \times GEFF_{ik} \times GEFF_i.\end{aligned} \tag{20}$$

The first term, EFF_{ik}, is the true efficiency change that is based on the group-type technical efficiency. The second term, $GEFF_{ik}$, is the measured change of the technology gap between the group-type frontier and the group-specific frontier, whereas $GEFF_i$ is the measured change of the technology gap between the group-specific frontier and the metafrontier. what is the point of this Footnote

? seems confusing[10] The latter two terms summarize the change of the overall efficiency due to varying technology gaps between the hierarchy levels. We call them heterogeneity components.

Next, we disentangle the overall technology change, represented by $TECH^b$ in (18), into the group-type technology change and heterogeneity components. Using (15), we have

$$\begin{aligned} TECH^b &= \frac{y_{ik}^c\left(\mathbf{x}^b\right)}{y_{ik}^b\left(\mathbf{x}^b\right)} \frac{g_{ik}^b\left(\mathbf{x}^b\right)}{g_{ik}^c\left(\mathbf{x}^b\right)} \frac{g_i^b\left(\mathbf{x}^b\right)}{g_i^c\left(\mathbf{x}^b\right)} \\ &= TECH_{ik}^b \times GTECH_{ik}^b \times GTECH_i^b. \end{aligned} \tag{21}$$

The first term, $TECH_{ik}^b$, is the change of the group-type technology evaluated at the input mix observed at time b. The next two terms measure the changes of the technology gaps between the hierarchy levels: $GTECH_{ik}^b$ for the gap between the group-type frontier and the group-specific frontier whereas $GTECH_i^b$ for the gap between the group-specific frontier and the metafrontier, both evaluated at $\mathbf{x}^b$. Note that in order to achieve overall technology progress, either the group-type technology experiences progression, or the technology progress is faster at the upper-levels of the hierarchy, resulting in lower technology gap ratios at time c.

In a similar manner, the overall input change effect $KACC^b$ in (18′) can be decomposed into the input change effect of the group-type technology and two heterogeneity components. That is,

$$\begin{aligned} KACC^b &= \frac{y_{ik}^b\left(\mathbf{x}^c\right)}{y_{ik}^b\left(\mathbf{x}^b\right)} \frac{g_{ik}^b\left(\mathbf{x}^b\right)}{g_{ik}^b\left(\mathbf{x}^c\right)} \frac{g_i^b\left(\mathbf{x}^b\right)}{g_i^b\left(\mathbf{x}^c\right)} \\ &= KACC_{ik}^b \times GKACC_{ik}^b \times GKACC_i^b. \end{aligned} \tag{22}$$

The first term, $KACC_{ik}^b$, is the input change effect evaluated with the group-type technology at time b. The next two terms capture the changes of the technology gaps between the hierarchy levels due to the change of the input mix, when the technologies are all fixed at time b. Conceptually, if input change (e.g., capital deepening) increases the overall potential output ($KACC^b > 1$), this can be

[10] Note that each of these two terms can be further decomposed into an effect due to relative technology change and another effect due to input change. Taking $GEFF_{ik}$ for example, it can be written as $GEFF_{ik} = \frac{g_{ik}^c(\mathbf{x}^c)}{g_{ik}^b(\mathbf{x}^b)} = \frac{g_{ik}^c\left(\mathbf{x}^b\right)}{g_{ik}^b\left(\mathbf{x}^b\right)} \frac{g_{ik}^c(\mathbf{x}^c)}{g_{ik}^c(\mathbf{x}^b)}$. The first term captures the change of the gap between two production frontiers, holding the input mix fixed at $\mathbf{x}^b$, whereas the second term measures the change of the gap due to the change of the input mix, when both production frontiers are positioned at time c. Using notations to be introduced shortly, $GEFF_{ik} = \frac{1}{GTECH_{ik}^b} \frac{1}{GKACC_{ik}^c}$.

achieved via two separate channels. First, the potential output is increased at the group-type level ($KACC_{ik}^b > 1$). Second, even if the group-type potential output remains unchanged, as far as the technology gaps are larger (smaller value) when evaluated at the new input mix ($\mathbf{x}^c$), the overall potential output increases. There are two technology gaps in our three-level hierarchy setting, contributing to the two heterogeneity components.

If we evaluate (21) at $\mathbf{x}^c$ instead of $\mathbf{x}^b$, we end up with the decomposition of $TECH^c$. Similarly, if we use the technologies at time c to evaluate the potential outputs and technology gaps in (22), we obtain the decomposition of $KACC^c$. They are

$$TECH^c = TECH_{ik}^c \times GTECH_{ik}^c \times GTECH_i^c, \tag{21'}$$

$$KACC^c = KACC_{ik}^c \times GKACC_{ik}^c \times GKACC_i^c. \tag{22'}$$

With (20–22′), we obtain the following new decomposition:

$$\begin{aligned}\frac{y^c}{y^b} = (EFF_{ik} \times GEFF_{ik} \times GEFF_i) \times (TECH_{ik} \times GTECH_{ik} \times GTECH_i) \\ \times (KACC_{ik} \times GKACC_{ik} \times GKACC_i).\end{aligned} \tag{23}$$

2.5 Estimation

Assume that for two time periods b and c, we observe N_{ik} DMUs of type k in group i, where $k = 1, \ldots, K_i$ and $i = 1, \ldots, I$. For these data, it suffices to estimate the following potential output values to define all our technical efficiency and technology gap ratios: $y_{ik}^{t_2}(\mathbf{x}^{t_1})$, $y_i^{t_2}(\mathbf{x}^{t_1})$, and $y^{t_2}(\mathbf{x}^{t_1})$, where $t_1, t_2 \in \{b, c\}$ and $\mathbf{x}^{t_1}$ is the input mix of one of the N_{ik} DMUs at time t_1. Different methods could be used at this stage. We prefer, given our context, to make use of a nonparametric estimation method. Indeed, there is no guideline to define the technology (captured by output requirement sets) in the multi-group and multi-type context. Moreover, assuming a specific technology structure could bias the results of our study.

As such, we estimate the potential outputs using a Data Envelopment Analysis (DEA)-based methodology. DEA, introduced by Charnes et al. (1978), does not assume any functional form for the technology, but rather reconstructs the technology using the data. Nevertheless, to avoid a trivial reconstruction and to comply with the common practice, we impose some regularity conditions on the technology.[11] Clearly, stochastic methods could be used as an alternative at this stage, when a parametric form is specified (Amsler, O'Donnell, & Schmidt, 2017).

With DEA, the three potential outputs can be obtained by means of linear programs. Let's start with the group-type potential output. For each firm n of type k in group i, let's denote its input-ouput mix at time t by $(\mathbf{x}^t_{ikn}, y^t_{ikn})$. For any input mix $\mathbf{x}$, the group-type potential output $y^t_{ik}(\mathbf{x})$ is obtained using the following linear program:

$$\begin{aligned} y^t_{ik}(\mathbf{x}) = \max_{\lambda_1,\ldots,\lambda_{N_{ik}}} & \; y \\ \text{(C-1)} & \; y \leq \sum_{n=1}^{N_{ik}} \lambda_n y^t_{ikn}, \\ \text{(C-2)} & \; \mathbf{x} \geq \sum_{n=1}^{N_{ik}} \lambda_n \mathbf{x}^t_{ikn}, \\ \text{(C-3)} & \; \sum_{n=1}^{N_{ik}} \lambda_n = 1, \\ \text{(C-4)} & \; \forall n = 1, \ldots, N_{ik} : \lambda_n \geq 0, \\ \text{(C-5)} & \; y \geq 0. \end{aligned} \tag{24}$$

The other two potential outputs are iteratively estimated as

$$\begin{aligned} y^t_i(\mathbf{x}) &= \max_{k \in \{1,\ldots,K_i\}} y^t_{ik}(\mathbf{x}), \\ y^t(\mathbf{x}) &= \max_{i \in \{1,\ldots,I\}} y^t_i(\mathbf{x}). \end{aligned}$$

may add a remark here that it is non-convex, see Mohsen Afsharian, Victor V. Podinovski EJOR These estimators have to be interpreted as their theoretical counterparts.

As a final remark, we point out that, in general, linear programs are very sensitive to the presence of outliers. Indeed, all the peers are used when computing potential outputs. Fortunately, it is possible to make the linear programs robust to this issue. Well-established methods, discussed, for example, in Daraio and Simar (2007), are the order-m (where m can be viewed as a trimming parameter), and the order-α (analogous to traditional quantile functions) procedures. In words,

[11] In particular, we assume that the output-requirement sets satisfy free disposal of outputs, and are compact (Färe & Primont, 1995). Also, refer to O'Donnell et al. (2008) and Huang, Ting, Lin, and Lin (2013) for more detail about the estimation of technology gap ratios. Finally, we point out that imposing regularity conditions is weaker than relying on a parametric specification for the technology/production function.

these procedures use sub-samples of the observations to compute the potential outputs in the linear programs. As a result, the estimates are less sensitive to potential issues, i.e., more robust.

3 Application

We investigate the sources of labor productivity growth in China's manufacturing industry, while distinguishing between different technology groups and ownership types. We start by presenting the data, and contextualizing our study by showing some key descriptive statistics. Next, we provide our results for the growth decomposition. Finally, we link our results to the findings in the literature and discuss policy implications.

3.1 Data and descriptive statistics

Our study uses the China Industry Survey (CIS) dataset, which is a firm-level dataset prepared by the National Bureau of Statistics of China. It comprises more than 555,000 distinct firms and spans the years 1998–2007, providing over two million observations. The CIS dataset provides rich information about each firm, including industrial classification, ownership structure, and inputs and outputs. Because of its comprehensiveness and wide coverage, the CIS dataset is highly visible among recent studies on China's industry (Brandt et al., 2012; M. Chen & Guariglia, 2013; Hsieh & Klenow, 2009; Yu, 2015) remove M..

Considering technology heterogeneity, we divide the sample into industrial sectors and then by ownership types. In compliance with the national standard of economic classification (GB/T 4754), each firm in the CIS dataset receives a four-digit industry classification code, with which we define 30 sectors. Based on the classification of technology intensities made by the Organization for Economic Cooperation and Development (OECD), we re-group the sectors into three technology groups: low-tech, medium-tech, and high-tech.[12] The industrial sectors and their technology classification are presented in Table S1 of the supplementary material. The CIS dataset defines 29 registration types based on ownership and organization structure. To focus on the ownership structure, we summarize them

[12]The OECD classification can be found at http://www.oecd.org/sti/ind/48350231.pdf. We remove art ware and other manufacturing (code range 4211–4290) from the sample because the technology intensity of this sector is undefined. We also remove tobacco manufacturing (code range 1610–1690) because this sector is dominated by state-owned firms. Both sectors are small compared to others.

into three types: state-owned, private-owned, and foreign-owned.[13] Because the registration information is often ambiguous about control rights and sometimes misleading (Hsieh & Song, 2015), we adopt a two-step procedure to determine a firm's ownership type. In step one, a firm is defined as state- (private-, or foreign-) owned if the majority of the registered capital is owned by the state and collective organization (private persons, or foreigners). If step one is indeterminate, the registration type is used to determine the ownership type as far as it is unambiguous about control rights.[14]

We consider a very simple setting with two production factors: capital and labor. The corresponding output variable is industrial value added. This simple setting, which dates to Solow (1956), is highly visible in empirical studies (Brandt et al., 2012; M. Chen & Guariglia, 2013; Kumar & Russell, 2002) remove M.. Although the CIS dataset provides information on labor input, capital input and value add are reported in nominal values. We follow the procedure of Brandt et al. (2012) to convert capital stock from original purchasing prices to real values. We also use their sector-specific output deflator to convert value added into real terms.[15]

After removing incomplete firm-level observations, we end up with 496,642 distinct firms and a total of 1,862,703 observations. In Table 1, we present the summary statistics of the three ownership types and the three technology groups for years 1998, 2003, and 2007.

The total firm numbers are 79.2–85.3% of those reported by the *China Statistical Yearbook*, whereas the aggregate employment numbers are 73.9–80.8% of the yearbook values. These indicate good coverage of our dataset despite that we dropped two sectors. Judging by employment, the share of state-owned firms declined rapidly from 68.8% to 20.1%, whereas that of private firms and foreign-owned firms increased sharply. This dramatic change can be explained by China's FDI-friendly industrial policy after 1992 and the massive enterprise

[13] Many studies also define a fourth ownership type: collective ownership. Firms are collective-owned if they are under control of collective organizations, such as government bureaus and communes. Therefore, collective ownership is conceptually similar to state ownership. Empirically, collective- and state-owned firms are found to be similar in many aspects (M. Chen & Guariglia, 2013; Guariglia et al., 2011; Walheer & He, in press). To simplify our hierarchy structure, we merge collective ownership into state ownership.

[14] Firms registered as state-owned enterprises, state-owned partnerships, state-owned limited liability companies, collective enterprises, and collective partnerships are defined as state-owned; firms registered as sole proprietorships, private partnerships, private limited liability companies, and private joint-stock companies are defined as private-owned; firms registered as (wholly) foreign-owned are defined as foreign-owned.

[15] We refer the reader to Brandt, Van Biesebroeck, and Zhang (2014) for more detail.

Table 1: Descriptive statistics by ownership type and technology intensity

Year	State	Private	Foreign	Low tech	Medium tech	High tech	Aggregate
			Firm number (percentages for sub categories)				
1998	58.42	27.57	14.01	38.54	55.08	6.37	130668
2003	26.30	55.24	18.46	37.51	55.74	6.75	167461
2007	10.20	70.69	19.12	36.06	57.17	6.77	287312
			Employment (percentages for sub categories)				
1998	68.81	18.53	12.66	32.82	60.03	7.15	45789757
2003	38.72	37.54	23.74	35.70	54.85	9.46	45708566
2007	20.07	47.96	31.97	35.20	52.47	12.33	63599564
			Capital per worker				
1998	80.75	46.77	107.90	55.42	90.07	78.76	77.89
2003	132.96	63.00	108.31	65.18	122.97	107.14	100.84
2007	202.91	86.39	123.09	76.78	152.85	115.86	121.51
			Value added per worker				
1998	25.96	32.05	56.64	27.66	30.08	53.65	30.97
2003	64.04	60.04	92.41	48.94	74.53	115.57	69.27
2007	136.52	111.09	127.16	86.23	135.46	161.43	121.33

Units: persons for total employment and 1,000 RMB per person for capital per worker and value added per worker. We report sample means for capital per worker and value added per worker.

reform launched in 1997 (Hsieh & Song, 2015; K. H. Zhang & Song, 2001) remove K. H.. Although the majority of the firms are found in the low-tech and medium-tech sectors, there has been a dramatic increase in the employment share of the high-tech group.

Overall, we observe substantial capital deepening in China's manufacturing industry. The average capital-labor ratio increased from 77,890 RMB per person to 121,510 RMB per person, or a 56% increase, yet this is not comparable to the increase in labor productivity, which is 292%. Capital intensity and labor productivity are markedly different between ownership types and technology groups. Foreign ownership, which was the most capital intensive in 1998, was overtaken by state ownership in 2007. Similarly the productivity advantage of foreign ownership vanished in 2007. Capital deepening was strong among medium- and high-tech firms, but to a much less extent for low-tech firms. The productivity gap was reduced between low- and high-tech firms but increased for low-tech firms. Thus, we observe productivity convergence across ownership types but mixed result between technology groups.

Our formal analysis is based on aggregate data at the sector-ownership level. That is, all firms belonging to an ownership type in a two-digit sector is aggregated into a single DMU better to not refer to DMU in this Section; industry firms etc... This aggregation strategy is based on two considerations. First, DEA is sensitive to outliers and extreme values. Because we observe very large and very small firms at the same time, a firm-level analysis will impair the reliability of the entire set of estimates. Second, growth decomposition investigates the performance change of DMUs over time, which requires a balanced panel. However, the CIS dataset is highly unbalanced, with unusually high entry/exit rates in certain years (Brandt et al., 2014). Therefore, aggregation is a necessary strategy to overcome this data problem. Because we have 27 two-digit sectors and three ownership types, in total we end up with 81 sector-ownership combinations (DMUs).

3.2 Results

short intro here ?

Productivity convergence To take a first look at the growth pattern, we report the average labor productivity in 1998 and 2007 as well as the average labor productivity growth rate in Table 2.[16]

Table 2: Labor productivity growth per ownership and technology group

Technology Intensity	Ownership	Labor productivity 1998	Labor productivity 2007	Labor productivity growth
low	state	25.41	104.48	309.69
	private	31.32	93.96	197.93
	foreign	52.87	106.91	91.43
	all	36.53	101.78	199.68
medium	state	29.34	134.81	387.67
	private	35.37	127.13	270.50
	foreign	66.39	190.30	179.22
	all	43.70	150.75	279.13
high	state	34.03	124.13	326.86
	private	49.74	153.02	236.81
	foreign	80.78	184.99	126.06
	all	54.85	154.05	229.91
all	state	28.26	121.27	349.14
	private	35.32	116.49	237.19
	foreign	62.48	155.74	137.55
	all	42.02	131.17	241.29

Units: 1,000 RMB per person for labor productivity and percent for productivity growth. We report the cumulative growth rates over 1998–2007, i.e., $\left(y^{2007}/y^{1998} - 1\right) \times 100\%$. We average over all DMUs (sector-ownership combinations) in the corresponding category to obtain these values.

Judging by the overall average, the labor productivity of China's manufacturing industry grew 241.29% over the 1998–2007 period. We observe a clear pattern of labor productivity catching up between ownership types. Within each technology group and on average, foreign ownership had the absolute advantage in labor productivity in 1998, whereas state ownership was the least productive.

[16]The values for all 81 sector-ownership combinations are reported in Table S2 of the supplementary material.

Although all three ownership types experienced phenomenal productivity growth, state ownership was the clear winner in terms of speed, followed by private ownership. Eventually, the productivity gap almost vanished within the low-tech group, and substantially reduced for the other two technology groups. Remarkably, with the exception of the high-tech group, state ownership outperformed private ownership on all grounds in 2007. Foreign ownership was still the leader in 2007, but the productivity advantage had been substantially reduced.

According to the average numbers, the high-tech group was the most productive and the low-tech group the least in 1998. During 1998–2007, labor productivity growth was much higher for the medium-tech group than the high-tech group. As a result, the productivity gap between the medium- and high-tech groups virtually disappeared in 2007, although the latter maintained its leading position. The productivity growth of the low-tech group, however, was the lowest among the three technology groups.

The above discussions reveal convergence of labor productivity between ownership types. They also suggest convergence between the medium- and high-tech groups, but divergence between the low-tech group and the rest of the industry. It remains to establish the overall growth pattern when we pool the data together. Following Kumar and Russell (2002), Henderson and Russell (2005), and Walheer (2018c), we plot the cumulative growth rate of labor productivity against labor productivity in 1998 along with the GLS regression line in Figure 1. The t-value for the slope coefficient is also displayed.

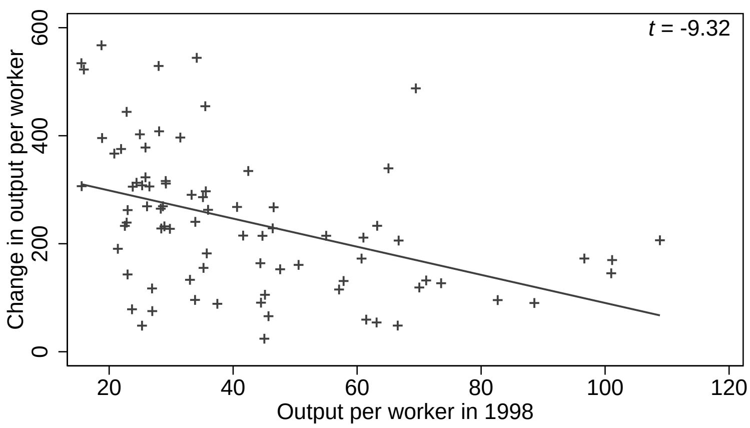


Figure 1: Labor productivity growth versus labor productivity in 1998

Figure 1 clearly indicates convergence of labor productivity in China's manufacturing industry. That is, in addition to convergence among ownership types, we demonstrate that convergence also holds when the industry is further divided into sectors within ownership types, i.e., when heterogeneity in the sectoral dimension is considered. The latter result has never been documented by the literature. In light of the sluggish productivity growth in the low-tech group, our result also shows that the converging force between ownership types dominated the divergent force of the low-tech group.

Efficiency change Our next step is to identify the driving force of the convergence pattern. In Table 3, we present the efficiency change effect in reference to different technology concepts: the meta technology (EFF), which assumes the same technology for all DMUs; the group-specific technologies (EFF_i), which assumes heterogeneity across technology groups but not over ownership types; and the group-type technologies (EFF_{ik}), which assumes full heterogeneity. We also present the heterogeneity components in (20), which are GEFF_i and GEFF_{ik}.[17] Next, in Figure 2 we plot the three efficiency change effects against labor productivity in 1998 and report the GLS t-values for the slope coefficients.

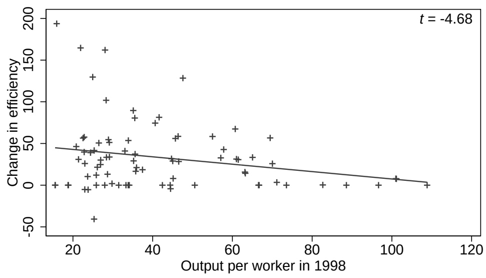
Table 3: Growth decomposition: the efficiency change effect

Technology intensity	Ownership	$\mathbf{y^{1998}}$	EFF	$\mathbf{EFF_i}$	$\mathbf{EFF_{ik}}$	$\mathbf{GEFF_i}$	$\mathbf{GEFF_{ik}}$
low	state	25.41	36.48	26.01	-3.89	8.09	32.64
	private	31.32	42.53	21.57	13.73	16.83	7.58
	foreign	52.87	12.51	11.51	7.54	2.48	4.88
	all	36.53	30.51	19.69	5.79	9.13	15.03
medium	state	29.34	15.27	9.13	0.84	4.45	8.08
	private	35.37	53.83	21.56	10.28	28.41	13.01
	foreign	66.39	33.45	31.52	30.41	2.57	1.44
	all	43.70	34.18	20.73	13.84	11.81	7.51
high	state	34.03	77.01	55.62	39.61	9.13	17.58
	private	49.74	26.54	20.00	20.00	4.96	0.00
	foreign	80.78	10.92	9.61	0.00	1.01	9.61
	all	54.85	38.15	28.41	19.87	5.03	9.06
all	state	28.26	30.77	21.17	3.22	6.45	19.14
	private	35.32	46.19	21.39	12.76	21.09	9.35
	foreign	62.48	22.42	20.93	17.72	2.36	3.75
	all	42.02	33.13	21.16	11.23	9.97	10.75

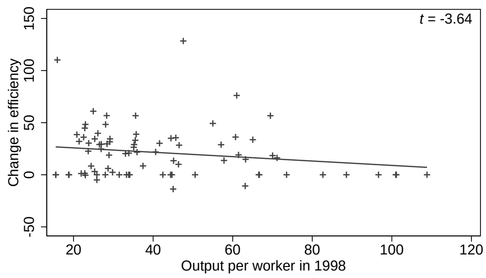
y^{1998} represents output per worker in 1998 (unit: 1,000 RMB per person). EFF and related variables are evaluated over the 1998–2007 period and converted into cumulative growth rates (unit: percent). That is, $\text{EFF} = \left(\frac{e^{2007}(\mathbf{x}^{2007}, y^{2007})}{e^{1998}(\mathbf{x}^{1998}, y^{1998})} - 1\right) \times 100\%$, and similarly for the others. We average over all DMUs (sector-ownership combinations) in the corresponding category to obtain these values.

Judging by EFF_{ik}, the overall efficiency change is quite small (11.23%), indicating sluggish efficiency improvement when DMUs are benchmarked against the group-type frontiers. private firms improved their technical efficiency in all three technology groups. Foreign-owned firms improved their efficiency strongly

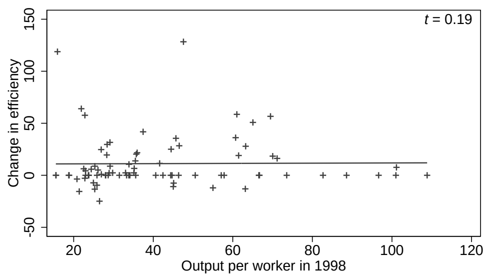
[17] The full results for all 81 sector-ownership combinations are reported in Table S3 of the supplementary material.



(a) EFF versus y^{1998}



(b) EFF_i versus y^{1998}



(c) EFF_{ik} versus y^{1998}

Figure 2: Efficiency change versus labor productivity in 1998

in the medium-tech group but to a less extent in the low-tech group. Overall, the efficiency improvement by these two ownership types were moderate. For state ownership, efficiency improvement is only seen in the high-tech group and very weak in average.

At this stage, we want to investigate why efficiency change was in general weak, and especially weak for state ownership. We offer two explanations. First, if the efficiency levels were already high in 1998, then we cannot expect any strong improvement afterwards. Second, poor initial efficiency level could coexist with weak efficiency change. To find out which argument is true, we present the efficiency levels in Table 4.

The numbers clearly support the first explanation. In almost all categories, EFF_{ik} is large in Table 3 only if e_{ik}^{1998} is relatively low in Table 4. Note that the average efficiency level for state ownership was already 0.912 in 1998, which leaves little room for further improvement. This explains why efficiency change was particularly low for state ownership. It is also clear that the efficiency levels of most categories were quite close to unity in 2007. Thus, future efficiency improvement is even more difficult. The second explanation only works for state ownership in the low-tech group, for which the efficiency level was low in 1998, and the subsequent efficiency change was negative.

The three measures of efficiency change are linked by the heterogeneity compo-

Table 4: Technical efficiency in 1998 and 2007

Technology intensity	Ownership	e_{ik}^{1998}	e_{ik}^{2007}
low	state	0.893	0.861
	private	0.839	0.942
	foreign	0.874	0.923
	all	0.869	0.909
medium	state	0.950	0.951
	private	0.914	0.991
	foreign	0.764	0.942
	all	0.876	0.961
high	state	0.818	0.997
	private	0.827	0.975
	foreign	1.000	1.000
	all	0.882	0.991
all	state	0.912	0.919
	private	0.874	0.969
	foreign	0.835	0.940
	all	0.874	0.943

We average over all DMUs (sector-ownership combinations) in the corresponding category to obtain these values.

nents GEFF_{ik} and GEFF_i through (20). As we explained there, GEFF_{ik} measures by how much the observed technology gap between the production frontiers of the ownership (lower level) and the technology group (upper level) has closed up, whereas GEFF_i measures the gap-closing rate between the group frontier (low level) and the meta frontier (upper level). Stronger technology progress at the lower level or favorable input change is needed to reduce these gaps.

The positive numbers of the heterogeneity components indicate industry wide gap-closing between the production frontiers at different hierarchy levels. Consequently, the efficiency change effect becomes much stronger when DMUs are benchmarked against the group frontier (EFF_i) or the meta frontier (EFF). If measured by EFF, the average efficiency change (33.13%) is three times as large as the average EFF_{ik}. We point out that the difference between these estimates should not be interpreted as a bias. Instead, it reflects a difference in interpretation: If we use the meta frontier as the reference, then technology gaps become part of the efficiency measure.

The result for GEFF_{ik} shows that state-ownership was able to substantially close up their technology gaps with respect to the low- and high-tech group frontiers (large GEFF_{ik}). Thus, they receive much higher scores in EFF_i than EFF_{ik} in these groups and in general. The same is true for private ownership of the medium-tech group. Next, when we consider GEFF_i, we find that private ownership successfully reduced the gap between the group frontier and the meta frontier in low- and medium-tech groups. Consequently they score much higher in EFF than EFF_i. The same is true for state ownership in the high-tech group. Remarkably, the heterogeneity components are almost always the smallest for foreign ownership.

When we contrast EFF_{ik} with y^{1998}, a negative correlation is only seen in the high-tech group but not the others. Actually, they show a positive correlation when the numbers are averaged at the group level or by ownership. These observations explain Figure 2c: Efficiency change measured by EFF_{ik} does not contribute to labor productivity convergence at all. The previous discussion shows that categories with lower labor productivity in 1998 (i.e., state-low-tech, state-high-tech, private-low-tech, and private-medium-tech) receive higher scores in the heterogeneity components, which boosts up their efficiency change when the latter is measure by EFF_i or EFF. Thus, the heterogeneity components generate a permutation effect on EFF_i and EFF: In almost all cases, private ownership beats foreign ownership in efficiency change, and in three cases, state ownership also beats private ownership. These explain why we observe significant convergence of efficiency change in Figures 2a and 2b. Clearly, the reduced technology gaps of the low-productivity categories contribute to these convergence patterns.

In conclusion, when benchmarked against the group-type production frontiers, the efficiency change was quite small in magnitude and it barely contributed to labor productivity convergence. This happened because the efficiency levels were already high in 1998. In reference to group frontiers or the meta frontier, efficiency change becomes much larger and exhibits convergence. These are due to the shrinking technology gaps between the hierarchy levels, which prevailed all categories but were unbalanced.

Technology change Next, we inquire the role played by technology change. Similar to what we did earlier, we first present in Table 5 our three measures of the technology change effect (TECH, TECH_i, and TECH_{ik}) along with the heterogeneity components (GTECH_i and GTECH_{ik}).[18] To assess the impact of technology change on labor productivity convergence, in Figure 3 we generate the scatter plots for the technology change measures versus labor productivity in 1998. GLS regression lines and t-values are shown therein.

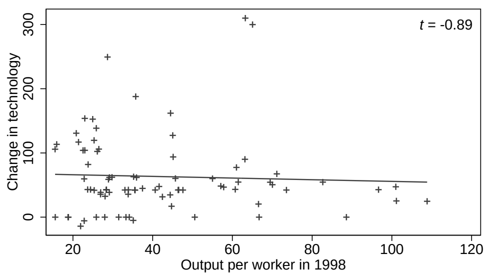
The numbers reported for TECH_{ik} indicate strong technology progress in all technology groups and for all ownership types. According to the average in the last row, labor productivity grew 62.47% as a result of pure technology progress that

[18]The full results for all 81 sector-ownership combinations are presented in Table S4 of the supplementary metarial.

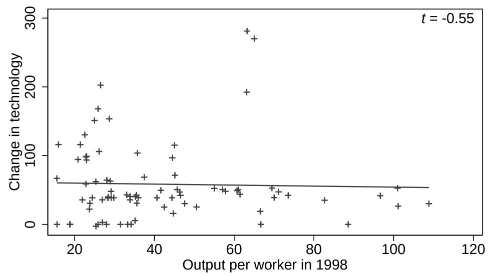
Table 5: Growth decomposition: the technology change effect

Technology intensity	Ownership	$\mathbf{y^{1998}}$	TECH	$\mathbf{TECH_i}$	$\mathbf{TECH_{ik}}$	$\mathbf{GTECH_i}$	$\mathbf{GTECH_{ik}}$
low	state	25.41	82.53	92.94	130.94	-3.36	-9.70
	private	31.32	46.14	45.73	52.09	-0.24	-3.99
	foreign	52.87	76.17	67.64	42.75	8.87	18.94
	all	36.53	68.28	68.77	75.26	1.76	1.75
medium	state	29.34	61.23	45.18	66.91	8.56	-0.80
	private	35.37	41.66	35.65	38.41	5.11	-0.24
	foreign	66.39	89.25	77.93	66.11	5.73	7.42
	all	43.70	64.05	52.92	57.14	6.46	2.13
high	state	34.03	51.82	57.39	48.70	-4.27	8.34
	private	49.74	41.08	44.13	36.22	-2.05	6.24
	foreign	80.78	30.41	30.77	30.88	-0.23	-0.09
	all	54.85	41.10	44.10	38.60	-2.18	4.83
all	state	28.26	68.86	65.99	90.97	2.28	-3.41
	private	35.32	43.42	40.70	43.74	2.13	-1.05
	foreign	62.48	77.38	68.50	52.68	6.35	11.28
	all	42.02	63.22	58.40	62.47	3.59	2.27

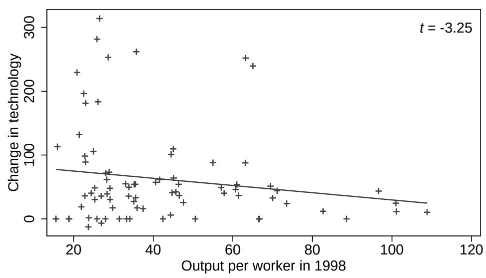
y^{1998} represents output per worker in 1998 (unit: 1,000 RMB per person). TECH and related variables are evaluated over the 1998–2007 period and converted into cumulative growth rates (unit: percent). That is, $\text{TECH} = \left(\sqrt{\frac{y^{2007}(\mathbf{x}^{1998})}{y^{1998}(\mathbf{x}^{1998})}\frac{y^{2007}(\mathbf{x}^{2007})}{y^{1998}(\mathbf{x}^{2007})}} - 1\right) \times 100\%$, and similarly for the others. We average over all DMUs (sector-ownership combinations) in the corresponding category to obtain these values.



(a) TECH versus y^{1998}



(b) TECH_i versus y^{1998}



(c) TECH_{ik} versus y^{1998}

Figure 3: Technology change versus labor productivity in 1998

originated from the "bottom" of the technology hierarchy. Note that this effect is 4.5 times stronger than that of efficiency change identified in Table 3, when both concepts are defined in reference to the group-type production frontiers. When we distinguish between ownerships, we find that technology progress was much stronger for state ownership, which is true within technology groups and on average. Private ownership outperformed foreign ownership in the low- and high-tech groups. According to the group averages, technology progress was strongest in the low-tech group and weakest in the high-tech group. In conjugation with the rankings of y^{1998}, the observations made here suggest convergence in technology progress, i.e., less productive categories in 1998 achieved higher rates of technology growth afterwards. This conjecture is readily justified by Figure 3c. Thus, when the group-type technologies are considered, technology progress contributed to labor productivity growth and the convergence of labor productivity at the same time.

The two heterogeneity components GTECH_{ik} and GTECH_i capture gap closing/widening between production frontiers at different hierarchy levels. These effects are generated by the movement of the production frontiers, whereas the impact of input change has been purged out. A positive value indicates expansion of the technology gap with respect to the upper-level production frontier and a negative value represents closing up of the gap. Judging by the average values, which are 2.27% for GTECH_{ik} and 3.59% for GTECH_i, the technology gaps enlarged only slightly. That is, on average, the group-type frontiers, the group frontiers, and the meta frontier shifted out almost uniformly. This explains why the three measures of the technology change effect are highly similar.

According to the values of GTECH_{ik} and GTECH_i, state ownership closed (expanded) their technology gaps with respect to the upper-level production frontier more (less) than private ownership, and private ownership closed (expanded) their technology gaps more (less) than foreign ownership. These relationships are true in most cases. Thus, GTECH_{ik} and GTECH_i tend to drive down (raise) TECH_i and TECH more (less) for state ownership than for private ownership. The same is true when we compare private ownership and foreign ownership. Thus, the heterogeneity components generate a permutation effect on TECH_i and TECH: They often reduce the technology change effect for categories that were less productive in 1998. Consequently, in Figures 3a and 3b, the negative relationship between the technology change effect and labor productivity in 1998 virtually disappears.

To summarize, we observe unbalanced change in the technology gaps between the hierarchical technology frontiers. State ownership reduced their technology gaps with respect to the group frontiers and the meta frontier, but the opposite is true for foreign ownership. Although the average technology change effect is insensitive to the choice of the reference technology, the latter does affect the convergence pattern of the former.

Capital deepening Finally, we present the results for the capital deepening effect. As before, we present the three measures of the capital deepening effect (KACC, KACC_i, and KACC_{ik}) along with the two heterogeneity components (GKACC_i and GKACC_{ik}) in Table 6.[19] Next, we investigate the convergence of capital deepening in Figure 4.

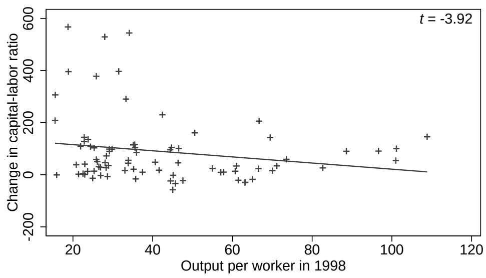
Table 6: Growth decomposition: the capital deepening effect

Technology intensity	Ownership	$\mathbf{y^{1998}}$	KACC	$\mathbf{KACC_i}$	$\mathbf{KACC_{ik}}$	$\mathbf{GKACC_i}$	$\mathbf{GKACC_{ik}}$
low	state	25.41	102.26	106.97	132.92	-0.84	-10.12
	private	31.32	50.96	72.05	74.83	-9.93	-1.84
	foreign	52.87	4.66	10.55	36.79	-3.78	-16.90
	all	36.53	52.63	63.19	81.51	-4.85	-9.62
medium	state	29.34	264.85	280.54	310.66	-7.86	0.83
	private	35.37	79.10	132.05	147.94	-20.78	-6.75
	foreign	66.39	26.64	33.61	46.05	-6.63	-7.41
	all	43.70	123.53	148.73	168.22	-11.76	-4.44
high	state	34.03	87.93	79.69	130.96	0.94	-17.53
	private	49.74	86.34	91.49	102.01	-2.42	-5.56
	foreign	80.78	63.48	64.54	74.86	-0.76	-7.29
	all	54.85	79.25	78.57	102.61	-0.75	-10.13
all	state	28.26	178.95	187.51	218.28	-4.02	-5.67
	private	35.32	68.44	103.10	113.05	-14.32	-4.62
	foreign	62.48	21.78	27.65	45.48	-4.82	-11.26
	all	42.02	89.72	106.09	125.60	-7.72	-7.18

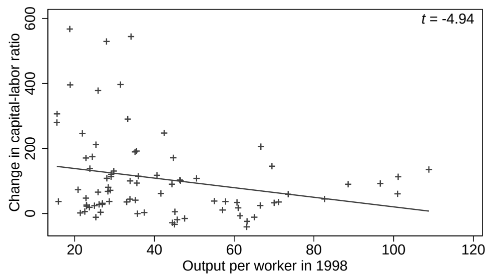
y^{1998} represents output per worker in 1998 (unit: 1,000 RMB per person). KACC and related variables are evaluated over the 1998–2007 period and converted into cumulative growth rates (unit: percent). That is, $\text{KACC} = \left(\sqrt{\frac{y^{1998}(\mathbf{x}^{2007})}{y^{1998}(\mathbf{x}^{1998})}\frac{y^{2007}(\mathbf{x}^{2007})}{y^{2007}(\mathbf{x}^{1998})}} - 1\right) \times 100\%$, and similarly for the others. We average over all DMUs (sector-ownership combinations) in the corresponding category to obtain these values.

As before, we start our analysis with KACC_{ik}, the measure for the capital deepening effect based on the group-type technology. Judging by the overall average, which is 125.60%, this effect is twice as large as the efficiency change effect. According to this number, China's manufacturing would be able to increase its labor productivity by 125.60% times through capital deepening alone, even if there had been zilch efficiency or technology improvement. Clearly, it was the main driver for productivity growth. The magnitude of this effect is quite large for state ownership, usually twice as large as that of private ownership, and almost four time larger than that of foreign ownership. This pattern remind us of Table 1.

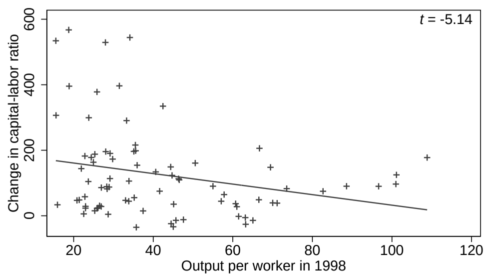
[19]The full results for all 81 sector-ownership combinations are presented in Table S5 of the supplementary material.



(a) KACC versus y^{1998}



(b) $KACC_i$ versus y^{1998}



(c) $KACC_{ik}$ versus y^{1998}

Figure 4: Capital deepening versus labor productivity in 1998

There we find much more rapid growth in the capital-labor ratio among domestic firms, which explains the stronger effects observed here.

Because the capital deepening effect is always the strongest for state ownership and the weakest for foreign ownership, if we relate this to the productivity rankings, a negative correlation between $KACC_{ik}$ and y^{1998} emerges. Thus, we do observe convergence of the capital deepening effect across ownership types. At the group level, however, the low-tech group had not only the lowest labor productivity in 1998, but also the smallest $KACC_{ik}$ value, which suggests divergence. This pattern looks highly similar to what we have seen in Table 2. It turns out that the converging force is stronger than the divergence force when pooling all DMUs together: Figure 4c depicts a negative relationship between $KACC_{ik}$ and y^{1998} that is highly significant.

The heterogeneity components $GKACC_{ik}$ and $GKACC_i$ capture the change in technology gaps when the upper- and lower-level production frontiers are held constant but the input mix is allowed to change. A positive value means a widening gap in reference to the upper-level production frontier, whereas a negative value implies that the gap has narrowed. Table 6 shows that the technology gaps between the hierarchy levels have been closing up for almost all categories. Judging by the average values, which are -7.18% for $GKACC_{ik}$ and -7.72% for $GKACC_i$, the average technology gap between the hierarchy levels were narrowed as a result of capital deepening. This explains why the capital deepening effect becomes smaller when the group or meta technology is used as the benchmark. We point out that the heterogeneity components are not negligible in the current case. The average capital deepening effect along the meta frontier (KACC) is almost 30% smaller than that along the group-type frontiers (125.60% versus 89.72%).

Between technology groups or ownership types, the heterogeneity components GKACC_{ik} and GKACC_i do not display any particular pattern that is similar to what we have observed in Tables 3 and 5. Consequently, the permutation effect on KACC_i and KACC is generally missing.[20] This explains why the convergence pattern portrayed by Figure 4c is barely altered when we switch to KACC_i and KACC (Figures 4a and 4b).

To conclude, the capital deepening effect played the dominant role in labor productivity growth. It also strongly contribute to labor productivity convergence. Capital deepening resulted in smaller technology gaps between the hierarchy levels for almost all categories. Although the heterogeneity components are moderately large, they do not alter the qualitative results.

3.3 Summary and discussion

We summarize our findings as follows:

First, China's manufacturing industry experienced vigorous labor productivity growth over the 1998–2007 period. On average, the growth rate was 241.29%. Productivity growth was highly unbalanced across technology groups or ownership types. It exhibited a strong convergence pattern between ownership types and between the medium- and high-tech groups. However, the productivity gap between the low-tech group and the rest of the industry enlarged. Overall, we observe strong convergence in labor productivity in China's manufacturing industry between sectors and ownership types.

Second, depending on the reference production frontier, productivity growth due to efficiency change was 11.23–33.13%. The measured effect is stronger when benchmarked against the group frontiers or the meat frontier because the observed technology gaps between the hierarchical levels shrank over time. In reference to the group-type technologies, there was little efficiency change among state-owned firms and in the low-tech group, but less productive categories usually benefited more from the gap-closing effects. Efficiency change contributed to productivity

[20] We point out that GKACC_{ik} is quite large in size for state ownership in the high-tech group and foreign ownership in the low-tech group, which reduces KACC_i substantively for these categories. The same is true for GKACC_i on private ownership in the medium-tech group.

convergence only if it is measured by the group technologies or the meta technology.

Third, the measured technology change effect, which ranges 58.40–63.22%, is less sensitive to the choice of the reference technology. On average, the technology gaps between the hierarchy levels expanded very little (2.27% and 3.59%). At the group-type level, the technology change effect was stronger among less productive categories (e.g., 90.97% for state ownership and 75.26% for the low-tech group). At higher levels, however, the more productive categories often benefited more from the expansion of technology gaps. The technology change effect exhibits convergence only at the group-type level.

Fourth, capital deepening was the major driver of productivity growth and convergence. In reference to the group-type technologies, productivity growth due to capital deepening was 125.60%. Because capital deepening also narrowed down the technology gaps between the hierarchy levels, it is smaller when measured by the group technologies (106.09%) or the meta technology (89.72%). Capital deepening narrowed down technology gaps on almost all fronts and this effect outweighs the gap expansion effect brought by technology change. Convergence is seen in all three measures of the capital deepening effect.

At this stage, we want to contrast our results with the relevant findings in the literature. First, our DEA-based tripartite decomposition highlights capital deepening as the most important single factor for labor productivity growth. This finding is consistent with Henderson et al. (2007) and Badunenko and Tochkov (2010), although they study Chinese regions. However, regressional analysis of China's industry emphasize the importance of TFP in explaining output growth (Brandt et al., 2012; S. Chen et al., 2011). remove S. We think the difference can be reconciled on the following grounds. One, the growth mode of the overall economy may differ from that of the manufacturing sector. In fact, our decomposition assigns far more importance to efficiency change and technology change than studies on regional economies.[21] Second, if we interpret TFP change as the composite effect of efficiency change and technology change (Bos, Economidou, & Koetter, 2010; Henderson & Russell, 2005), our estimates suggest a TFP growth rate similar to what has been estimated for China's industry using regressional methods.[22] Third, following the previous interpretation, our results do show that

[21]If we ignore technology heterogeneity, as most studies do, then our efficiency change, technology progress, and capital deepening effects are 33.13%, 63.22%, and 89.72%, respectively. These numbers are 17.2%, 6.0%, and 101.5% in Henderson et al. (2007) and -8.18%, 6.82%, and 55.56% in Badunenko and Tochkov (2010).

[22]Ignoring technology heterogeneity again, our estimates suggest that cumulative TFP growth

TFP contributed more than capital accumulation to labor productivity growth.[23]

Second, our analyses reveal strong convergence of labor productivity, which is quite clear across ownership types. Similarly, Berkowitz et al. (2017), Hsieh and Song (2015), and Jefferson et al. (2008) all find TFP convergence across ownership types. In a broader sense, our finding is also consistent with those of Deng and Jefferson (2011) and Lemoine et al. (2015), who show convergence of industrial labor productivity across regions. These findings, however, are at odds with studies of China's regional economic development. Badunenko and Tochkov (2010) and Henderson et al. (2007) study per capita GDP growth among Chinese provinces using decomposition methods that are very similar to ours. Their results show divergence over 1998–2003 and 1990–2000, which was mainly driven by efficiency change and technology change.[24] In a similar study, K.-H. Chen et al. (2009) remove K. H. study TFP growth among Chinese provinces. Their decomposition also demonstrates a divergence pattern driven by efficiency change and technology change. This seemingly conflict is reconciled by Rodrik (2013), who argues that the manufacturing industry should exhibit unconditional convergence because this industry produces tradable goods and faces fierce competition domestically and abroad. Consequently, firms are under constant pressure to upgrade their operations and remain competitive. It follows that resource reallocation and technology transfer are easier to take place, resulting in productivity convergence. In contrast, the rest of the economy (agriculture and service) is locked to the local market, which means the mechanisms for convergence do not function properly. This explains why the economy as a whole usually fails to exhibit convergence.

These findings have rich policy implications. First, the convergence patterns identified in this article suggest that the market forces were functioning properly in China's manufacturing industry. That is, capital intensity increased in low-productivity sectors, where the marginal return was higher (Figure 4c), and

was 117.29% during 1998–2007, or 9.00% per annum. In comparison, Brandt et al. (2012) estimate that the annual TFP growth rate was 7.96% during the same period, whereas Jefferson et al.'s (2008) estimate is 9.39%. These numbers are much higher than the TFP growth rates estimated for Chinese regions (Brandt & Zhu, 2010; K.-H. Chen, Huang, & Yang, 2009), which provides further evidence that the growth mode of the overall economy differs from that of the manufacturing sector.

[23]That is, cumulative TFP growth was 117.29% whereas the capital deepening effect was 89.72% when we ignore technology heterogeneity. In comparison, Brandt et al. (2012) estimate that TFP growth contributed to 57% of the output growth in China's manufacturing industry, and the remaining 43% was due to factor accumulation. Nevertheless, we remark that our decomposition is not directly comparable to theirs.

[24]Unel and Zebregs (2009) perform a similar analysis using much earlier data (1978–1998), their analysis produces a convergence pattern only after the much stronger growth in coastal provinces and the effect of foreign direct investment have been controlled.

technology spillover took place between high-tech and low-tech categories (Figure 3c). Regarding resource reallocation, both Brandt et al. (2012) and Ding et al. (2016) emphasize firm turnover, which is especially true for state ownership (Jefferson et al., 2008). In addition, Hsieh and Song (2015) point out that state-owned firms successfully reduced redundant labor. For channels of technology spillover, Xu and Sheng (2012) highlight the role of foreign-owned firms, whereas He and Walheer (in press) identify additional sources: high-tech sectors, private ownership, and exporting firms. Overall, China's marketization reforms has successfully boosted labor productivity and reduced disparity in the manufacturing industry.

Second, the main driver of productivity growth in China's manufacturing industry is capital deepening. This is similar to the growth pattern of the Asian Tigers, but very different from that of the OECD countries, where technology change is often found to play an equally important role (Badunenko & Romero-Ávila, 2013; Henderson & Russell, 2005; Kumar & Russell, 2002; Walheer, 2016a, 2016b). Badunenko and Tochkov (2010) and Henderson et al. (2007) question the sustainability of this growth mode. We point out that although the capital intensity of China's manufacturing industry was almost quadrupled during 1998–2007 (Table 1), it was still far less than that of the developed economies, which was 210,566 USD per person in the United States, 22 million Yen per person in Japan, and 106,779 Euro per person in EU12.[25] Based on these numbers, China's manufacturing industry can maintain another 15 years' high growth by means of capital deepening alone.

At the same time, the three ownership types follow different growth paths. Domestic firms were far more reliant on capital accumulation than foreign-owned firms, whereas state-owned firms were far more capital-thirsty than indigenous private firms (Table 6). The fast capital accumulation among private firms is justifiable, because their capital intensity has been the lowest (Table 1). However, capital accumulation among state-owned firms seems to contradict the principle of optimal resource allocation, because they were already the most capital intensity in 2003, and they further increased their advantage in 2007. Resource allocation could be improved if more capital were allocated to indigenous private firms.

Third, technology change played a far more important role in productivity growth than efficiency change.[26] However, it does not mean China's manufacturing

[25]Source: OECD Stan Dataset and authors' own calculations. Values reflect real capital stock (in 2010 currency values) per worker in the manufacturing industry in 2007. EU12 does not include Spain and Portugal because of missing data in capital stock.

[26]This conclusion is based on comparing EFF_{ik} in Table 3 to TECH_{ik} in Table 5. According to our previous discussions, they are appropriate measure for pure efficiency change and technology

did a poor job in improving technical efficiency or efficiency change could be a potential source of future labor productivity growth. Overall, efficiency growth was weak simply because there was little room for improvement, which was even less in 2007. Our result suggests that the ultimate source of labor productivity growth in China's manufacturing industry must be technology progress, if not capital accumulation. The only exception seems to be state ownership in the low-tech group, for which efficiency change could play a more important role than in other categories.

Finally, we express our concerns about the low-tech group. Initial labor productivity and subsequent productivity growth were both the lowest among this group, suggesting divergence (Table 2). According to the tripartite decomposition, low productivity growth of the low-tech group were caused by sluggish efficiency growth and capital accumulation (Tables 3 and 6). The weak efficiency growth is largely due to the efficiency regression of state ownership, but the low level of capital accumulation is seen among all three ownership types. Remarkably, the low-tech group also features the lowest capital intensity throughout the study period (Table 1). In the language of Bos, Economidou, and Koetter (2010), these observations suggest that the low-tech group may belong to a different technology club. Measures to improve technical efficiency, especially among state-owned firms, and policies that encourage capital accumulation may help the low-tech group to achieve higher labor productivity growth and narrow the gap with the rest of the manufacturing industry.

4 Conclusion

In this article, we employ DEA to analyze labor productivity growth in China's manufacturing industry during 1998–2007. Methodologically, we employ the concept of metafrontier to control for technology heterogeneity across technology groups and ownership types when we perform the tripartite decomposition. We highlight the importance of controlling for heterogeneity when making interpretations and explain how different decomposition results can be linked by the heterogeneity components. Empirically, our tripartite decomposition identifies capital deepening as the most important single factor for labor productivity growth, fol-

progress, because each DMU is contrasted with the potential output of the technology group it belongs to. In comparison, EFF_i and EFF contains the technology progress of the lower-level technology relative to the upper-level technology, whereas TECH_i and TECH reflect the technology progress of the upper-level frontiers.

lowed by technology progress, but the contribution from efficiency change was moderate. We find strong unconditional convergence of labor productivity during the study period, driven by capital deepening and technology change. However, we also observe increasing disparity between the low-tech group and the rest of the industry.

With these results we are able to reconcile two strands of literature. Specifically, we point out that the dispute over the relative importance of technology progress and factor accumulation in explaining China's productivity growth may arise because researchers use different data and measure technology differently. We also emphasize that the intrinsic difference between the manufacturing industry and the aggregate economy is the key to understand the convergence and divergence patterns found in the literature.

We think China's industrial reforms successfully created a healthy market environment in which resource reallocation and technology transfer contributed to labor productivity convergence, but we also express our concerns over state ownership and the low-tech sectors. The former received too much capital whereas the latter were given too little. We are cautiously optimistic about China's capital-driven industrial growth, yet we point out that the source of long-term productivity growth must be technology progress.

Before concluding, we would like to point out a few limitations of the study. First, due to data limitation, our decomposition does not consider human capital, which has been found to be an important source of productivity growth (Badunenko & Romero-Ávila, 2013; Henderson & Russell, 2005; Walheer, 2016a). Thus, our estimates could be biased.[27] Second, our categorization of technology groups is based on an exogenous criterion which is time-invariant. Endogenously determined dynamic regimes, as modeled by Bos, Economidou, and Koetter (2010) and Bos, Economidou, Koetter, and Kolari (2010), may more accurately model the technology differences between industrial sectors and bring new insights to the analysis. Finally, we must acknowledge that the Kumar-Russell style decomposition has its own limitations. That is, it cannot separate the effect of entry and exit from aggregate productivity growth, or study the effect of resource reallocation within sectors. Regressional methods are advantageous in answering these questions (Brandt et al., 2012; Ding et al., 2016).

[27]Nevertheless, Walheer (2019b) shows that the bias might be small in the Chinese context.

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