Spillovers and path dependences in the Chinese manufacturing industry: A firm-level analysis

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ABSTRACT
In China, numerous policy interventions have been undertaken to promote exports of the manufacturing industry. In this paper, we study how the burgeoning export sector has affected the performance of the manufacturing industry. In particular, we focus our attention on two dimensions: efficiency and technological advancement, and the presence of spillovers and path dependences. The main feature of our empirical study is to distinguish between different types of firms according to their output orientation, ownership, and technology intensity. We also recognize that outputs for domestic use and exports may be produced using different technologies. Our results demonstrate the superiority of multi-output firms in both efficiency and technological advancement. Further, these firms generate strong outgoing spillovers to the industry. In contrast, export-only firms are found to be the most inefficient and technologically underdeveloped, while barely generating outgoing spillovers. In terms of efficiency and technological advancement, we also find that foreign- and privately-owned firms and high-tech firms are the best performers. Finally, we find evidence of strong path dependence and weak absorptive capacities for incoming spillovers in the manufacturing industry. We give targeted policy recommendations based on these findings.

KEYWORDS
China; Manufacturing industry; Technology gap; Technical efficiency; Spillover; Path dependence

JEL CLASSIFICATION
C14; D24; F14; L60; P31; O5

1. Introduction

China's rapid economic development led the country to become the world's largest exporter in 2009. As of 2016, China's exports of merchandise reached $2.1 trillion, accounting for 13.2% of the world's total and 18.6% of China's gross domestic product (United Nations, 2017). This important ascension is mainly due to the strong manufacturing industry in China. China replaced the US as the world's largest manufacturer in 2010, and has solidified its position ever since. In 2015, the total value added of the manufacturing industry was $3.25 trillion or 26.7% of the world's total (World

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Bank Open Data). All these facts highlight why China is often called the *factory of the world*.

The importance of international trade for boosting economic growth has long been recognized by Chinese policymakers. Indeed, various measures have been undertaken at different levels to stimulate exports. At the top of the list of measures is the massive value added tax (VAT) rebate program. The program, introduced in 1985, exempts most exported merchandise from VAT.[1] Following this, special economic zones (SEZs) were established, specifically designed to attract foreign direct investment (FDI) and promote exports. To date, China has 219 national SEZs hosting 78 national bonded zones and 63 national export processing zones. These zones are dedicated to export-oriented manufacturing.[2] Finally, financial conveniences are provided to exporters through state-owned financial institutions.[3]

From a macroeconomic perspective, exports are viewed as an engine for economic growth (Jarreau & Poncet, 2012; United Nations, 2016; Zhang & Felmingham, 2002) and for efficiency and productivity gains (Caliendo & Rossi-Hansberg, 2012; Melitz, 2003). From a microeconomic perspective, a positive relationship between export status and firm performance is assumed–exporters are viewed as larger, more capital intensive, paying higher wages, and more productive than non-exporters (Bai, Krishna, & Ma, 2017; Bernard & Jensen, 1995, 1999; Bigsten & Gebreeyesus, 2009; De Loecker, 2007). Given the huge amount of resources spent on export-promotion programs in China, it is important to empirically test whether these various measures have been accompanied by the expected outcomes. In other words, we wish to test whether Chinese firms engaging in the export market demonstrate efficiency advantages and technological advancement over firms that are focused on the domestic market. A second aspect of our investigation is to verify whether the presence of exporters has a positive effect in terms of efficiency and technological gains for non-exporters. In other words, we investigate the presence of spillovers between firms. Finally, we test for the presence of path dependences for firm efficiency and technological advancement. The presence of spillovers and path dependences also presents a major reason for policy interventions.

The main distinguishing feature of our empirical study is to recognize that different types of firms coexist in China. In particular, we consider three characteristics of firms. An important characteristic of China's manufacturing industry is the prolificity of exporters. Based on export status, most previous works partitioned firms into exporters and non-exporters. However, the reality is more complex, as a substantial fraction of exporters also serve the domestic market–that is, they are multi-output producers.[4] Similar to Lu, Lu, & Tao (2010), we recognize three types of firms: domestic firms, export-only firms and multi-output firms. A second distinctive feature of China's manufacturing industry is the coexistence of different ownership status. We follow the literature (Brandt, van Biesebroeck, & Zhang, 2012; Hsieh & Song, 2015) and consider four ownership statuses for our analysis: state, collective, private and foreign. This distinction has been overlooked in most previous empirical works about the exports-efficiency nexus.[5] Finally, the last feature of China's manufacturing industry is the rapid export sophistication, in both absolute terms (Rodrik, 2006; Schott, 2008) and relative terms (Amiti & Freund, 2010; Upward, Wang, & Zheng, 2013). Therefore, we also partition firms with respect to their technology intensity.[6] Overall, considering the firm specificities allows us to conduct a more realistic and fair analysis, while avoiding bias of omitting important characteristics.

Besides distinguishing between different types of firms, we also recognize that domestic and export outputs are potentially produced using different technologies and production factors. While previous works have acknowledged that outputs have been modified for foreign consumption before exporting (Bernard & Jensen, 1999), no distinction has been made on the technology side.[7] We believe that this modelling represents an important restriction in the Chinese case. First, ample evidence suggests that at least some Chinese exports are produced using a different technology.[8] Second, the Chinese manufacturing sector is populated with numerous foreign-owned firms that are active exporters.[9] Trade theory usually assumes that multinationals have different (superior) technology than do domestic firms (Helpman, Melitz, & Yeaple, 2004; Markusen, 2002). Third, we recognize that the production of domestic outputs and exports are linked by shared and non-shared inputs in the production process.[10] Indeed, while some inputs are used jointly to produce both types of outputs (typical examples are factories, machines and infrastructure), other inputs are allocated between the two production processes (typical examples are employees, materials and other variable inputs). Hence the former gives rise to economies of scale and economies of scope (Nehring & Puppe, 2004; Panzar & Willig, 1977, 1981) in the production process, while the latter constrains the production of the outputs. For these reasons, we model heterogeneous technologies for the production of domestic outputs and exports, while acknowledging their connection by considering shared and non-shared inputs. We believe this representation improves the realism of the analysis. As a robustness test, we also analyze a benchmark case where both outputs are produced under a common technology.

Finally, our empirical analysis distinguishes itself from previous works by the dataset used and the estimation method. Our definitions of efficiency and technology advancement are based on the concept of meta-technology introduced by Battese & Rao (2002).[11] This technique is designed to study efficiency and technology advancement when firms are split into groups of heterogeneous technologies. Meta-technology-based methods have been widely used to study various topics in China, including industrial sectors (see, among others, Chen & Huang, 2011; Li, Kopsakangas-Savolainen, Xiao, & Lau, 2017; Lin & Zhao, 2016; Zhang & Choi, 2013; Zhang & Wei, 2015). These studies commonly used aggregate-level (macro) data, and relied only on a single criterion to partition firms. In contrast, we use firm-level (micro) data, and apply three criteria to define the groups. Moreover, the concept of meta-technology is not designed to study firms that produce two types of outputs. As such, we propose a simple modification of the original concept of meta-technology to allow for that opportunity. We use a robust nonparametric technique to estimate firm-level efficiency and technology gap. The conventional approach used in previous works was to parameterize a production function. However, choosing a specific functional form is not always innocuous (Choi, Lee, & Williams, 2011; Hsieh & Klenow, 2009; van Beveren, 2012), and is rather complex in light of our modelling of the firm production process.

The rest of this article is organized as follows. Section 2 introduces the methodology, while Section 3 presents our empirical investigation of the Chinese manufacturing industry. Finally, Section 4 presents our conclusion.

2. Methodology

We consider that we observe firms that are partitioned into M groups. We also assume that each group m contains K_m firms, and that every firm k produces a total output quantity, y_{mk}. The distinguishing feature of our method is to recognize the multi-output nature of the firms by dividing the total output quantity into domestic and export output quantities: $y_{mk} = y^d_{mk} + y^e_{mk}$. Finally, we assume that, for every firm k, the domestic output is produced using the inputs $\mathbf{x}^d_{mk}$, while the export output is produced using the inputs $\mathbf{x}^e_{mk}$. This implies that some inputs are jointly used to produce both outputs (when they appear in both $\mathbf{x}^d_{mk}$ and $\mathbf{x}^e_{mk}$), while others are allocated to specific output productions (when they appear in $\mathbf{x}^d_{mk}$ or $\mathbf{x}^e_{mk}$).

Our aim is to define measurements of efficiency and technological advancement for the total output quantity, y_{mk}, yet also for the domestic and export output quantities, y^d_{mk} and y^e_{mk}. While the former has been extensively studied in previous work, this is not the case for the latter. To define our measurements, we model each output type separately by its own technology. We begin by defining our notion of efficiency ratios, and then introduce the concept of technological gap ratios. Finally, we explain how the ratios can be computed by means of linear programs.

2.1. Efficiency

We define the technology in terms of output requirement sets. The output requirement sets for the domestic and export outputs for firm k in group m are defined as follows:

$$P^d_m(\mathbf{x}^d_{mk}) = \{y^d \mid \mathbf{x}^d_{mk} \text{ can produce } y^d\}. \tag{1}$$
$$P^e_m(\mathbf{x}^e_{mk}) = \{y^e \mid \mathbf{x}^e_{mk} \text{ can produce } y^e\}. \tag{2}$$

The sets $P^d_m(\mathbf{x}^d_{mk})$ and $P^e_m(\mathbf{x}^e_{mk})$ contain all the combinations of the outputs that can be produced by the input quantities, $\mathbf{x}^d_{mk}$ and $\mathbf{x}^e_{mk}$, respectively. These sets are interconnected because some inputs are used to produce both outputs, while other inputs are allocated between the output production processes.

Based on the definitions of the technology sets, we can define our concept of potential outputs. In particular, this is given for the domestic and export outputs of firm k in group m by:

$$y^d_m(\mathbf{x}^d_{mk}) = \max\left\{y^d \mid y^d \in P^d_m(\mathbf{x}^d_{mk})\right\}. \tag{3}$$
$$y^e_m(\mathbf{x}^e_{mk}) = \max\left\{y^e \mid y^e \in P^e_m(\mathbf{x}^e_{mk})\right\}. \tag{4}$$

Intuitively, we have that $y^d_m(\mathbf{x}^d_{mk}) \geq y^d_{mk}$ and $y^e_m(\mathbf{x}^e_{mk}) \geq y^e_{mk}$. When $y^d_m(\mathbf{x}^d_{mk}) = y^d_{mk}$, it reveals that the domestic production is at its optimal level, given the level of inputs $\mathbf{x}^d_{mk}$ and the technology captured by $P^d_m(\mathbf{x}^d_{mk})$. When $y^d_m(\mathbf{x}^d_{mk}) > y^d_{mk}$, it reflects possible output improvement without modifying the input levels. A similar interpretation holds true for $y^e_m(\mathbf{x}^e_{mk})$.

When there is potential output improvement, a natural and well-established indicator is the notion of the Debreu (1951)–Farell (1957) efficiency ratio, defined for firm k in group m as follows:

$$ER^d_m(\mathbf{x}^d_{mk}) = \frac{y^d_{mk}}{y^d_m(\mathbf{x}^d_{mk})}. \tag{5}$$
$$ER^e_m(\mathbf{x}^e_{mk}) = \frac{y^e_{mk}}{y^e_m(\mathbf{x}^e_{mk})}. \tag{6}$$

The relationships previously established between the actual and potential outputs imply that the efficiency ratios are, by construction, smaller than 1. When they are equal to 1, this means that the outputs are at their optimal level. In other words, it implies that firm k lies at the frontier of group m. Smaller values imply more inefficient behaviour, and thus more potential output improvement.

Attractively, we can also construct an efficiency ratio for the total output level using only the domestic- and export-level concepts. Let us define $y_m(\mathbf{x}^d_{mk}, \mathbf{x}^e_{mk})$ as the total level for the potential output. An initial observation is that the following relationship holds true for every firm k in group m:

$$y_m(\mathbf{x}^d_{mk}, \mathbf{x}^e_{mk}) = y^d_m(\mathbf{x}^d_{mk}) + y^e_m(\mathbf{x}^e_{mk}). \tag{7}$$

In other words, total potential output is equal to the sum of potential domestic and export outputs. This is an intuitive result that parallels $y_{mk} = y^d_{mk} + y^e_{mk}$ in potential output terms. Thus, a natural counterpart for the efficiency ratio is defined for total output, for every firm k in category m, as follows:

$$ER_m(\mathbf{x}^d_{mk}, \mathbf{x}^e_{mk}) = \frac{y_{mk}}{y_m(\mathbf{x}^d_{mk}, \mathbf{x}^e_{mk})} = \frac{y^d_{mk} + y^e_{mk}}{y^d_m(\mathbf{x}^d_{mk}) + y^e_m(\mathbf{x}^e_{mk})}. \tag{8}$$

It turns out that $ER_m(\mathbf{x}^d_{mk}, \mathbf{x}^e_{mk})$ only depends on actual and potential domestic and export outputs. Given that $y^d_m(\mathbf{x}^d_{mk}) \geq y^d_{mk}$ and $y^e_m(\mathbf{x}^e_{mk}) \geq y^e_{mk}$, this implies that $y^d_m(\mathbf{x}^d_{mk}) + y^e_m(\mathbf{x}^e_{mk}) \geq y^d_{mk} + y^e_{mk}$. As such, $ER_m(\mathbf{x}^d_{mk}, \mathbf{x}^e_{mk})$ is also smaller than 1 by construction. When $ER_m(\mathbf{x}^d_{mk}, \mathbf{x}^e_{mk}) = 1$, this implies that both the domestic and export outputs are at their optimal level. Conversely, $ER_m(\mathbf{x}^d_{mk}, \mathbf{x}^e_{mk}) < 1$ reflects potential output improvements. The cause for the inefficient behaviour can be investigated using $ER^d_m(\mathbf{x}^d_{mk})$ and $ER^e_m(\mathbf{x}^e_{mk})$.

2.2. Technological advancement

To define our concept of technological gap ratio, we make the hypothetical assumption of homogeneity between all firms. In practice, this is achieved by defining a common technology set grouping all firms. This is defined for firm k as follows:

$$P^d(\mathbf{x}^d_{mk}) = \left\{ P^d_1(\mathbf{x}^d_{mk}) \cup \cdots \cup P^d_M(\mathbf{x}^d_{mk}) \right\}. \tag{9}$$

$$P^e(\mathbf{x}^e_{mk}) = \left\{ P^e_1(\mathbf{x}^e_{mk}) \cup \cdots \cup P^e_M(\mathbf{x}^e_{mk}) \right\}. \tag{10}$$

Thus, $P^d(\mathbf{x}^d_{mk})$ and $P^e(\mathbf{x}^e_{mk})$ are the envelopment of the group-specific output requirement sets. They are also known as the meta-technology sets (see O'Donnell, Rao, & Battese, 2008). Potential outputs based on these output requirement sets are given, for firm k, by:

$$y^d(\mathbf{x}^d_{mk}) = \max \left\{ y^d \mid y^d \in P^d(\mathbf{x}^d_{mk}) \right\}. \tag{11}$$

$$y^e(\mathbf{x}^e_{mk}) = \max \left\{ y^e \mid y^e \in P^e(\mathbf{x}^e_{mk}) \right\}. \tag{12}$$

We again have $y^d(\mathbf{x}^d_{mk}) \geq y^d_{mk}$ and $y^e(\mathbf{x}^e_{mk}) \geq y^e_{mk}$. Moreover, potential outputs with respect to the meta-technology sets are larger than potential outputs with respect to the group-specific technology sets–that is, $y^d(\mathbf{x}^d_{mk}) \geq y^d_m(\mathbf{x}^d_{mk})$ and $y^e(\mathbf{x}^e_{mk}) \geq y^e_m(\mathbf{x}^e_{mk})$ for every firm k. Intuitively, this follows from the envelopment nature of the meta-technology set.

We can now define our concept of technology gap ratio capturing the technological advancement of the firms. Following O'Donnell et al. (2008), it is given for the domestic and export outputs for every firm k as follows:

$$TGR_m^d(\mathbf{x}_{mk}^d) = \frac{y_m^d(\mathbf{x}_{mk}^d)}{y^d(\mathbf{x}_{mk}^d)}. \tag{13}$$

$$TGR_m^e(\mathbf{x}_{mk}^e) = \frac{y_m^e(\mathbf{x}_{mk}^e)}{y^e(\mathbf{x}_{mk}^e)}. \tag{14}$$

We obtain that both technology gap ratios are smaller than unity. This can be seen from the relationship between the potential outputs discussed previously. A value of 1 reveals that firm k represents the best technological practice or no technology gap, while smaller values reflect greater technological backwardness. Thus, the technology gap ratios capture the distance between the group-level frontiers and the meta-technology frontier.

Again, we can construct a ratio for the total output level using only the domestic and export potential and actual outputs. As a first step, we can obtain the potential output level with respect to the meta-technology set by summing the export and domestic potential outputs:

$$y(\mathbf{x}_{mk}^d, \mathbf{x}_{mk}^e) = y^d(\mathbf{x}_{mk}^d) + y^e(\mathbf{x}_{mk}^e). \tag{15}$$

Building on this relationship, we define the technology gap ratio for the total output production, for each firm k, as follows:

$$TGR_m(\mathbf{x}_{mk}^d, \mathbf{x}_{mk}^e) = \frac{y_m(\mathbf{x}_{mk}^d, \mathbf{x}_{mk}^e)}{y(\mathbf{x}_{mk}^d, \mathbf{x}_{mk}^e)} = \frac{y_m^d(\mathbf{x}_{mk}^d) + y_m^e(\mathbf{x}_{mk}^e)}{y^d(\mathbf{x}_{mk}^d) + y^e(\mathbf{x}_{mk}^e).}. \tag{16}$$

This ratio is smaller than 1. Indeed, because the potential output values with respect to the meta-technology set are always greater than those defined with respect to the group-specific technology sets, we obtain that $y^d(\mathbf{x}_{mk}^d) + y^e(\mathbf{x}_{mk}^e) \geq y_m^d(\mathbf{x}_{mk}^d) + y_m^e(\mathbf{x}_{mk}^e)$. A value of 1 means that no technology gap occurs for the total output production. When the ratio is smaller than 1, more detailed information about the technology gap can be obtained by investigating the values of $TGR_m^d(\mathbf{x}_{mk}^d)$ and $TGR_m^e(\mathbf{x}_{mk}^e)$.

2.3. Computation

Different strategies can be used to compute the potential outputs for the domestic and export outputs. We choose to rely on a robust nonparametric technique for that purpose. As such, we estimate the potential outputs using a data envelopment analysis (DEA)-based methodology. DEA was introduced by Charnes, Cooper, & Rhodes (1978), and does not assume any functional form for the technology, but rather reconstructs the technology using the data. Moreover, when using DEA, the potential outputs are given by means of linear programs. As discussed previously, the domestic and export output production processes are generally interconnected by shared and non-shared inputs. Thus, they must be computed simultaneously. We obtain the domestic and export-oriented potential outputs by maximizing the total potential outputs (see Equations 7 and 15).

For every firm $k_0 \in (1, \ldots, K_{m_0})$ in group $m_0 \in (1, \ldots, M)$, $y^d_{m_0}(\mathbf{x}^d_{m_0 k_0})$ and $y^e_{m_0}(\mathbf{x}^e_{m_0 k_0})$ are obtained using the following linear program:

$$
\begin{aligned}
y^d_{m_0}(\mathbf{x}^d_{m_0k_0}) + y^e_{m_0}(\mathbf{x}^e_{m_0k_0}) = \max_{\lambda^d_{m_0k}, \lambda^e_{m_0k}\ (k=1,\ldots,K_{m_0})} & \ y^d + y^e \\
& \text{(C-1) } y^d \leq \sum_{k=1}^{K_{m_0}} \lambda^d_{m_0k} y^d_{m_0k}, \\
& \text{(C-2) } y^e \leq \sum_{k=1}^{K_{m_0}} \lambda^e_{m_0k} y^e_{m_0k}, \\
& \text{(C-3) } \mathbf{x}^d_{m_0k_0} \geq \sum_{k=1}^{K_{m_0}} \lambda^d_{m_0k} \mathbf{x}^d_{m_0k}, \\
& \text{(C-4) } \mathbf{x}^e_{m_0k_0} \geq \sum_{k=1}^{K_{m_0}} \lambda^e_{m_0k} \mathbf{x}^e_{m_0k}, \\
& \text{(C-5) } \forall k : \lambda^d_{m_0k} \geq 0, \lambda^e_{m_0k} \geq 0, \\
& \text{(C-6) } y^d \geq 0, y^e \geq 0.
\end{aligned}
\tag{17}
$$

Similarly, we obtain $y^d(\mathbf{x}^d_{m_0k_0})$ and $y^e(\mathbf{x}^e_{m_0k_0})$ using the following linear program:

$$
\begin{aligned}
y^d(\mathbf{x}^d_{m_0k_0}) + y^e(\mathbf{x}^e_{m_0k_0}) = \max_{\lambda^d_{mk}, \lambda^e_{mk}\ (k=1,\ldots,K_m; m=1,\ldots,M)} & \ y^d + y^e \\
& \text{(C-1) } y^d \leq \sum_{m=1}^{M} \sum_{k=1}^{K_m} \lambda^d_{mk} y^d_{mk}, \\
& \text{(C-2) } y^e \leq \sum_{m=1}^{M} \sum_{k=1}^{K_m} \lambda^e_{mk} y^e_{mk}, \\
& \text{(C-3) } \mathbf{x}^d_{m_0k_0} \geq \sum_{m=1}^{M} \sum_{k=1}^{K_m} \lambda^d_{mk} \mathbf{x}^d_{mk}, \\
& \text{(C-4) } \mathbf{x}^e_{m_0k_0} \geq \sum_{m=1}^{M} \sum_{k=1}^{K_m} \lambda^e_{mk} \mathbf{x}^e_{mk}, \\
& \text{(C-5) } \forall m, \forall k : \lambda^d_{mk} \geq 0, \lambda^e_{mk} \geq 0, \\
& \text{(C-6) } y^d \geq 0, y^e \geq 0.
\end{aligned}
\tag{18}
$$

Therefore, Equation (17) is very similar to (18). The only differences is that, in (17), the peers are restricted to firms belonging to group m_0, while, in (18), all firms are considered peers. This directly follows from the hypothetical assumption of homogeneity between firms for the meta-technology (see Equations 9 and 10). The estimated efficiency and technology gap ratios are obtained by plugging in the estimated potential outputs in their theoretical counterpart. They must be interpreted in an analogous manner.

We end this section with four important remarks. First, in Equations (17) and (18), two different technologies are considered for the domestic and export outputs.

Second, in these two linear programs, we allow for constant returns-to-scale. We believe that this assumption is more reasonable for our empirical application, as it offers the option of comparing firms of different size.[12] Third, because Equations (17) and (18) use all observed peers to compute the potential outputs, they are generally sensitive to the presence of outliers and measurement errors. To reduce the influences of these potential issues, we use the well-established techniques discussed in Daraio & Simar (2007). Briefly, these methods use (random) subsamples to compute the potential outputs. The estimators are then obtained by taking the average of the subsample estimators. Fourth, the conventional treatment in the literature is to assume that the productions for domestic goods and exports share the same technology. In this case, the efficiency and technology measures are based on the total output, y_{mk}, the group potential output, $y_m(\mathbf{x}_{mk})$, and the meta-technology potential output, $y(\mathbf{x}_{mk})$. The relevant definitions and linear programs are provided in the supplementary material.

3. Application

We investigate the presence of spillovers and path dependences in China's manufacturing industry using a firm-level dataset. We start by presenting our dataset and input choice. Next, we contextualize our empirical study by presenting key descriptive statistics. Following this, we present our results for efficiency and technological gap ratios, and test whether spillovers and path dependences are present. Finally, we discuss the policy implications of our results.

3.1. Dataset and input choice

For this study, we employ the *China Industry Survey* (CIS) dataset prepared by the National Bureau of Statistics of China. In particular, we use the dataset available from 1999 to 2007. We refer to Brandt, van Biesebroeck, & Zhang (2014) for more detail about this dataset, and particularly for an extensive discussion about the challenges of working with this dataset. As discussed in the introduction, one distinguishing feature of our empirical investigation is to consider heterogeneity between firms. In particular, we partition firms according to their export status, technology intensity category and ownership status. The CIS dataset provides a four-digit industrial classification code for each firm. Based on the first two digits, we divide the firms into 30 sectors, ranging from agri-food processing (13) to recycling (43). We follow the definition of the Organisation for Economic Co-operation and Development (http://www.oecd.org/sti/ind/48350231.pdf) to classify sectors in terms of technology intensity. In particular, sectors are classified as low-tech (13 sectors), medium-low-tech (eight sectors), medium-high-tech (five sectors) and high-tech (three sectors).[13] We refer to Table S1 in the supplementary material for detailed information about the technology intensity classification of the 30 sectors. For the 1999 to 2007 period, although the total number of firms more than doubles (2.14 times), the technology intensity composition remains stable. Low-tech firms are always the largest in number (36.2 to 38.1%), followed by medium-high-tech firms (29.3 to 31.4%) and medium-low-tech firms (25.7 to 26.1%). High-tech firms constitute a small fraction of the sample (6.6 to 7.1%).

Firm ownership status is defined by either registration information (Brandt et al., 2012) or *de facto* control rights (Hsieh & Song, 2015). In practice, we determine ownership status by a two-step procedure that combines the information on control rights and registration status. In the first step, a firm is defined as state- (collective-, private- or foreign-) owned if the share of the registered capital owned by the state (collective organization, private persons or foreigners) outweighs the shares of the other owners. If the information on registered capital is insufficient, we move onto the second step, where registration information is used to define the firm ownership status.[14] With this procedure, 98% of the 2,022,264 observations have properly defined ownership status. During the 1999 to 2007 period, the fractions of state- and collective-owned firms dropped dramatically from 35.5% and 33.3% to 3.7% and 5.6%, while that of private-owned firms increased rapidly from 17.2 to 69.1%, and that of foreign-owned firms increased slowly from 13.1 to 18.9%. This pattern is consistent with the observations made elsewhere (e.g., Berkowitz, Ma, & Nishioka, 2017), and can be explained by China's enterprise reform launched in the mid-1990s.

We consider a very simple setting with two production factors: capital and labour.[15] While labour is simply measured by the annual average of employed persons, the measurement of capital stock requires much more elaboration. The CIS dataset does not report real capital stock, but only the nominal value without accounting for depreciation. Our computation of the real capital stock closely follows the three-stage procedure of Brandt et al. (2012).[16] Outputs (total and export) are also provided in nominal values. They are deflated by the industry-specific price indices developed by Brandt et al. (2012).

As discussed in the introduction, a particularity of our modelling is to consider two different technologies for the domestic output and exports. We consider that capital and labour enter differently into the production processes. In particular, we model capital as an input shared by the productions of both goods, and we model labour as an input that must be allocated between the two production processes.[17] Unfortunately, data for labour are only provided at the aggregate level in the CIS dataset. We suggest allocating labour by considering both the quantity and quality of the outputs–that is, more labour is needed when the quantity or quality of the output increases.[18] As such, we allocate the number of employees using the total revenue of each output, and these data are available in the CIS dataset.

3.2. Descriptive statistics

As an initial step, we contextualize our empirical study by presenting key descriptive statistics. We first use the following criterion to define our three categories of firms: domestic firms (firms without exports), export-only firms (firms without domestic output) and multi-output firms (firms that have positive domestic output and exports). Table S2 in the supplementary material presents the descriptive statistics when grouping all years. It can be seen that the majority (70.5 to 76.2%) of firms serve the domestic market only. Only a small fraction of the firms (6.2 to 8.7%) serve the foreign market exclusively. When weighted by output shares, multi-output firms export 26.3 to 33.2% of their total shipments (see Table S3 in the supplementary material). These numbers are comparable with those reported by Lu et al. (2010) on Chinese firms, yet are sizably larger than those reported by Bernard, Jensen, Redding, & Schott (2007) for US firms. This highlights the growing importance of exports for Chinese firms and for the Chinese economy in general. Moreover, it reveals the important role of mixed producers in China.

The summary statistics in Table S2 indicate that the three types of firms are very different in size, capital intensity and labour productivity. Judging by the outputs, multi-output firms are, on average, the largest–2.6 to 3.4 times larger than domestic firms, and 1.7 to 2.3 times larger than export-only firms. Judging by the capital-labour ratio, multi-output firms are the most capital-intensive and export-only firms are the least. The capital-labour ratio of multi-output firms is 2.9 to 3.6 times that of export-only firms. Similarly, the labour productivity of multi-output firms is always the highest, while that of export-only firms is the lowest.

The data indicate vibrant firm turnover during the period of study. Table S4 in the supplementary material displays the average annual transition rates between the different statuses. For any firm that operates in the current year, it is most likely to remain operating and retain its current type in the subsequent year. The switching rate is relatively high for export-only firms switching to multi-output firms (14%) and for multi-output firms switching to domestic firms (12%). These figures reflect the fact that many multi-output firms are operating at the margin–that is, they either have very high or very low export ratios. We observe high exit rates among all three types. Finally, the annual entry rate is 28%, with the percentages of the three types roughly the same as those of the population.

Next, we discriminate firms with respect to their ownership status in Table S5, and their technology intensity category in Table S6 (both available in the supplementary material). In these tables, we again consider our three types of firms: domestic, export-only and multi-output firms. The summary statistics in Table S5 demonstrate huge differences among the ownership groups. Foreign-owned firms are much more likely to be export-only or multi-output firms. This is consistent with the finding that many FDI firms are export oriented (see, for example, Whalley & Xin, 2010; Zhang & Song, 2001). Unsurprisingly, 66.7% of total exports are made by foreign-owned firms. This number is consistent with that of Lu et al. (2010), who reported 59.7 to 71.0% over the 1998 to 2005 period. Regardless of output orientation, state- and foreign-owned firms are generally much larger and more capital-intensive, while foreign- and private-owned firms always have higher labour productivity. Within each ownership group, we again observe a high capital-labour ratio for multi-output firms, and a lower capital-labour ratio for export-only firms. For labour productivity, multi-output firms continue to be the most productive for the state, collective and private ownership types, with foreign ownership status being the only exception.

The summary statistics in Table S6 indicate that low-tech and high-tech firms are much more likely to be export-only or multi-output producers. This corroborates the common observation that China exports large quantities of both low- and high-tech merchandise (see, for example, Amiti & Freund, 2010; Li, 2018). Interestingly, low- and high-tech firms also export much more (63.5% of total exports) than do medium-low-tech and medium-high-tech firms. Judging by the outputs, low-tech firms are the smallest, regardless of their production orientation. The capital intensity is particularly low for low-tech firms. As expected, labour productivity is much higher for high-tech firms, regardless of their product orientation.

These key descriptive statistics reveal substantial heterogeneity among firms of different production orientation, ownership status and technology intensity categories. In other words, they confirm the importance of considering the heterogeneity between firms and output orientation, and thus corroborate our modelling of the production process. In the next section, we investigate the efficiency and technology gap of different types of firms (multi-output, domestic and export-only), while considering their sector, ownership status and technology intensity category.

3.3. Results

We begin by presenting the results for the efficiency and technological advancement of the firms. Next, we investigate the presence of spillovers and path dependences.

3.3.1. Efficiency and technological advancement

Using Equations (17) and (18), we compute the efficiency and technology gap ratios for all firms when controlling for different types of heterogeneity. We start by presenting in Table 1 the average efficiency and technology gap ratios when distinguishing firms with respect to their production status.[19] As explained in Section 2, an advantage of allowing for different technologies for domestic and export outputs is that ratios can also be computed for each output individually. At this point, it is worth noting that this only represents an advantage for multi-output firms because, for single-output producers, the overall efficiency and technology gap ratios coincide with the domestic or export counterparts by construction.[20]

Table 1. Efficiency and technology gap ratios

Year	Type	TGR	TGR^d	TGR^e	ER	ER^d	ER^e
1999	Multi	0.82	0.86	0.79	0.75	0.79	0.70
	Domestic	0.70	0.70	-	0.65	0.65	-
	Exporter	0.66	-	0.66	0.62	-	0.62
2000	Multi	0.85	0.89	0.81	0.76	0.78	0.70
	Domestic	0.69	0.69	-	0.66	0.66	-
	Exporter	0.62	-	0.62	0.63	-	0.63
2001	Multi	0.84	0.88	0.80	0.77	0.79	0.71
	Domestic	0.72	0.72	-	0.66	0.66	-
	Exporter	0.65	-	0.65	0.64	-	0.64
2002	Multi	0.86	0.89	0.81	0.78	0.80	0.72
	Domestic	0.71	0.71	-	0.67	0.67	-
	Exporter	0.64	-	0.64	0.65	-	0.65
2003	Multi	0.85	0.89	0.80	0.79	0.81	0.73
	Domestic	0.72	0.72	-	0.66	0.66	-
	Exporter	0.68	-	0.68	0.68	-	0.68
2004	Multi	0.89	0.92	0.83	0.78	0.80	0.77
	Domestic	0.72	0.72	-	0.68	0.68	-
	Exporter	0.67	-	0.67	0.68	-	0.68
2005	Multi	0.88	0.91	0.85	0.77	0.80	0.75
	Domestic	0.73	0.73	-	0.69	0.69	-
	Exporter	0.69	-	0.69	0.70	-	0.70
2006	Multi	0.90	0.92	0.88	0.79	0.82	0.76
	Domestic	0.72	0.72	-	0.70	0.70	-
	Exporter	0.68	-	0.68	0.68	-	0.68
2007	Multi	0.90	0.93	0.88	0.78	0.81	0.76
	Domestic	0.73	0.73	-	0.71	0.71	-
	Exporter	0.69	-	0.69	0.68	-	0.68

Table 1 indicates that multi-output firms have a clear advantage over domestic firms and export-only firms in both technical efficiency and technological advancement. Thus, multi-output firms represent the best practice in the Chinese manufacturing industry. These results align with our summary statistics (Tables S2, S5 and S6) and are consistent with previous findings. In particular, our results endorse the finding that exporters are generally more productive than non-exporters (see, for example, Bernard & Jensen, 1995; Bernard et al., 2007; Kasahara & Lapham, 2013). Our finding that export-only firms are both the least efficient and least technologically advanced may seem puzzling (see Lu, 2010; Yang & He, 2014). Although we do not have direct evidence, we suspect that the lower performance of export-only firms is linked to processing trade.[21] As stated by Koopman, Wang, & Wei (2012) and Yu (2014), processing exporters typically import components from abroad and export the assembled final merchandise. As a distinct feature, processing exporters ship 100% of their output to foreign destinations. Thus, we have reason to believe that our definition of export-only firms mainly encompasses processing exporters. Recent evidence has shown that Chinese processing exporters are less productive than non-processing exporters or non-exporters (Dai, Maitra, & Yu, 2016), which may explain our finding regarding export-only firms.

It is worth considering why multi-output firms are the best performers. Existing theories propose two possible explanations: the self-selection hypothesis and the learning-by-doing hypothesis. The first hypothesis focuses on *ex-ante* differences in performance between switchers and non-switchers, while the second hypothesis postulates *ex-post* divergences in performance following entry into the export market (Wagner, 2012). To test these hypotheses, we focus on the 2003 subsample and create five subgroups: (1) firms that are domestic in 2003 and become multi-output at some point between 2004 and 2007 (switchers), (2) firms that remain multi-output throughout 2003 to 2007, (3) firms that remain domestic throughout 2003 to 2007 (non-switchers), (4) new multi-output entrants in 2003 and (5) new domestic entrants in 2003. To study the self-selection hypothesis, we compare the efficiency and technology gap ratios of Groups (1) and (3) in 2003. Higher performance for Group (1) supports the self-selection hypothesis. Likewise, higher performance for Group (4) over Group (5) also supports the self-selection hypothesis. Next, we compare the change in the performance of Groups (2) and (3) over the 2003 to 2007 period. A higher rate of change for Group (2) lends support to the learning-by-doing hypothesis.[22]

Different tests can be used at this stage. Following the nonparametric spirit of our estimation method, we rely on the Wilcoxon-Mann-Whitney test. The p-values for the tests are reported in Table 2 (top panel). These results indicate that domestic firms that switch to multi-output firms during 2004 to 2007 demonstrate significantly higher *ex-ante* technical efficiency and technology gap ratios than do non-switchers. The performance of multi-output entrants is also significantly better than that of domestic entrants in the same year (2003). Over the 2003 to 2007 period, the performance change is statistically indistinguishable between domestic incumbents and multi-output incumbents. Overall, our results lend strong support to the self-selection hypothesis, and reject the learning-by-doing hypothesis.

Table 2. Self-selection and learning-by-doing hypotheses

Type	**Multi vs domestic**	**2003**		$\boldsymbol{\Delta}_{2003-2007}$	
		TGR	*ER*	*TGR*	*ER*
Self-selection hypothesis					
Incumbent	Switcher>domestic	0.01	0.00	–	–
Entrant	Multi> domestic	0.00	0.00	–	–
Learning-by-doing hypothesis					
Incumbent	Multi > domestic	–	–	0.36	0.27

Type	**Exporter vs domestic**	**2003**		$\boldsymbol{\Delta}_{2003-2007}$	
		TGR	*ER*	*TGR*	*ER*
Self-selection hypothesis					
Incumbent	Domestic > switcher	0.00	0.07	–	–
Entrant	Domestic > exporter	0.01	0.03	–	–
Learning-by-doing hypothesis					
Incumbent	Domestic > exporter	–	–	0.51	0.40

A second important factor is to examine the unexpected low performance among export-only firms. Similar to the work above, we use the 2003 subsample to create another five groups; this time, the comparison is made between export-only firms and domestic firms. The p-values for the tests are reported in Table 2 (bottom panel).[23] The results suggest that domestic firms that switch to export-only firms exhibit significantly lower performance than do non-switchers.[24] We also find that domestic entrants have significantly higher performance than do export-only entrants. Finally, when comparing the performance changes of domestic incumbents with those of multi-output incumbents, we find that their difference is statistically insignificant. These results again support the self-selection hypothesis and reject the learning-by-doing hypothesis.

Overall, the tests in Table 2 reveal that more (less) efficient and more (less) technologically advanced domestic incumbents or new entrants self-select into the multi-output (export-only) type; however, once a firm is 'settled down', further experience as a multi-output (export-only) firm has little effect on performance gains. Equivalently, this indicates that, if a multi-output firm is forced to quit the export market, its performance premium is unlikely to go away immediately.

Next, we discriminate firms even more in Tables 3 and 4. In Table 3, firms are partitioned with respect to their ownership status, and, in Table 4, firms are split with respect to their technology intensity category.

Table 3. Efficiency and technology gap ratios per ownership status

Ownership	**Type**	TGR	TGR^d	TGR^e	ER	ER^d	ER^e
State	Multi	0.72	0.8	0.66	0.69	0.75	0.62
	Domestic	0.70	0.70	–	0.60	0.60	–
	Exporter	0.60	–	0.60	0.62	–	0.62
Private	Multi	0.89	0.90	0.88	0.78	0.8	0.76
	Domestic	0.82	0.82	–	0.71	0.71	–
	Exporter	0.65	–	0.65	0.7	–	0.7
Foreign	Multi	0.91	0.95	0.90	0.81	0.83	0.79
	Domestic	0.80	0.80	–	0.70	0.70	–
	Exporter	0.71	–	0.71	0.75	–	0.75
Collective	Multi	0.75	0.76	0.74	0.70	0.68	0.72
	Domestic	0.72	0.72	–	0.59	0.59	–
	Exporter	0.61	–	0.61	0.59	–	0.59

Table 4. Efficiency and technology gap ratios per technology intensity category

Technology intensity	**Type**	TGR	TGR^d	TGR^e	ER	ER^d	ER^e
Low	Multi	0.80	0.81	0.79	0.74	0.78	0.72
	Domestic	0.69	0.69	–	0.67	0.67	–
	Exporter	0.64	–	0.64	0.63	–	0.63
Medium-low	Multi	0.79	0.81	0.77	0.75	0.75	0.75
	Domestic	0.73	0.73	–	0.68	0.68	–
	Exporter	0.68	–	0.68	0.64	–	0.64
Medium-high	Multi	0.82	0.81	0.83	0.77	0.78	0.76
	Domestic	0.72	0.72	–	0.65	0.65	–
	Exporter	0.65	–	0.65	0.66	–	0.66
High	Multi	0.91	0.93	0.89	0.76	0.77	0.75
	Domestic	0.81	0.81	–	0.70	0.70	–
	Exporter	0.82	–	0.82	0.69	–	0.69

Overall, the supremacy of multi-output firms in the Chinese manufacturing industry is confirmed when ownership status (Table 3) and technology intensity (Table 4) are considered. These two tables also provide additional interesting results. In Table 3, we find that, regardless of output orientation, foreign-owned firms have the highest efficiency ratio, followed by private-owned firms. Likewise, the technology gap ratios are notably greater for foreign- and private-owned firms. These findings align with the superiority of the foreign and private ownership status found in previous work (see, for example, Berkowitz et al., 2017; Zhang, Zhang, & Zhao, 2001). We do not observe systematic variation for the efficiency ratio when the technology intensity increases in Table 4. However, the technology gap ratios are substantially higher among high-tech firms, regardless of their output orientation, meaning that high-tech firms indeed have greater technology content than do firms in other technology intensity categories.

3.3.2. Path dependences and spillovers

Before moving onto interpretation of the results, it is useful to explain the notions of spillover and path dependence in our context. The notion of path dependence can be traced back to David (1985), where it is defined as 'important influences upon the eventual outcome [that] can be exerted by temporally remote events'. Later, this term was widely used to describe the phenomenon in which future paths of a system are based on its current or past states. In economics, recent theoretical development and empirical evidence suggest that the evolution of technology exhibits path dependence (Aghion, Dechezleprêtre, Hemous, Martin, & Van Reenen, 2016; Redding, 2002). In the following, we use the same definition, yet distinguish between two types of path dependence. First, we consider the efficiency behaviour of the firm relative to the 'best practice' of the group (efficiency ratio). Second, we consider the best practice of the group relative to that of the meta-technology (technology gap ratio).

In productivity analysis, the term 'spillover' is usually used to describe the influence of a group of firms on the productivity of another group of firms through various channels (see, for example, Arzaghi & Henderson, 2008; Moretti, 2004; Smarzynska, 2004). As a major departure from the conventional definition, we use this term to describe the way the group-level technology frontiers interact with the meta-technology frontier. We can distinguish two types of connection between these two frontiers. A first aspect is to verify whether best performers (i.e., firms with greater efficiency ratios) define the meta-frontier over time. In that case, these firms generate outgoing spillovers from the group-level frontiers to the meta-frontier. A second aspect is to investigate whether firms that define the meta-frontier become highly efficient over time–that is, whether the meta-frontier generates incoming spillovers onto the groups. We refer to Tsekouras, Chatzistamoulou, Kounetas, & Broadstock (2016) and Walheer (2018a) for further detail about these two types of spillovers.

Measuring spillovers and path dependences is complex in our case, given our modelling of the firm production process and the multiple level of heterogeneity present between firms. Moreover, as we allow spillovers to be bidirectional, this creates the presence of endogeneity. Given the nonparametric spirit of our measures for the efficiency and technology gap ratios, we decide to continue on this path. In particular, we use the Spearman correlation coefficient to quantify how current efficiency and technology gap ratios are correlated to past values. This coefficient is nonparametric because it uses rank values instead of the actual values.[25] In practice, we use a one-year window to capture the time needed for efficiency and technology advancement to dissipate in the Chinese manufacturing industry.

Table 5 presents the Spearman correlation coefficients (p-values in parentheses) between current and past efficiency and technology gap ratios when pooling all years together. When the Spearman correlation coefficients are closer to 1–that is, when the p-values are closer to 0–it indicates that spillovers or path dependences are observed.

The results in Table 5 provide strong evidence for the presence of path dependences for both the efficiency and technology gap ratios. Overall, the Spearman correlation coefficients are high, positive, and highly significant. That is, if a firm was closer to the group-level technology frontier in the past, then it is highly likely that this firm is closer in the current year. A similar reasoning holds true for the technology gap ratio. However, we note that the path dependences are substantially weaker among

Table 5. Path dependences and spillovers

Type		Path dependence		Spillover	
	Current	*Past*	*Coefficient*	*Past*	*Coefficient*
Multi	TGR	TGR	0.68 (0.00)	ER	0.45 (0.00)
	TGR^d	TGR^d	0.70 (0.00)	ER^d	0.48 (0.00)
	TGR^e	TGR^e	0.62 (0.00)	ER^e	0.44 (0.00)
Domestic	TGR^d	TGR^d	0.82 (0.00)	ER^d	0.28 (0.00)
Exporter	TGR^e	TGR^e	0.75 (0.00)	ER^e	0.12 (0.19)
Multi	ER	ER	0.72 (0.00)	TGR	0.37 (0.00)
	ER^d	ER^d	0.82 (0.00)	TGR^d	0.32 (0.00)
	ER^e	ER^e	0.65 (0.00)	TGR^e	0.21 (0.00)
Domestic	ER^d	ER^d	0.81 (0.00)	TGR^d	0.35 (0.00)
Exporter	ER^e	ER^e	0.85 (0.00)	TGR^e	0.28 (0.00)

multi-output firms. In particular, the Spearman correlation coefficient for the efficiency ratios is 0.72 for multi-output firms, and increases to 0.81 and 0.85 for domestic firms and export-only firms, respectively. Similarly, the Spearman correlation coefficient for the technology gap ratios is 0.68 for multi-output firms, yet increases to 0.82 and 0.75 for domestic and export-only firms, respectively. Both results suggest considerable 'reshuffling' among multi-output firms–that is, the rank orders of the efficiency and technological gap ratios change more frequently for that firm type. These results corroborate our earlier finding that multi-output firms experience substantial expansion of the technology frontier (see Table 1). Overall, these results reveal the double edge of path dependence for the Chinese manufacturing industry. First, the high levels of path dependences explain why we observe stable efficiency and technology gap ratios over time. Second, high levels of path dependences for domestic and export-only firms suggest stagnancy of their efficient behaviour and lack of technological progress.

Next, the results in Table 5 also highlight the presence of spillovers in the Chinese manufacturing industry. An initial observation is that the Spearman correlation coefficients are smaller for the spillover effects than for the path dependences. This reveals the higher importance of the latter phenomenon. It is also clear that the spillover effects are strongest for multi-output firms in both directions (outgoing and incoming). For the outgoing spillover effects, the Spearman correlation coefficient is 0.45 for multi-output firms. This means that the meta-technology frontier benefits strongly from the technology of multi-output firms. In comparison, the outgoing spillover effect from domestic firms is much weaker in magnitude (0.28), yet remains significant, while the outgoing spillover effect from exporters is the weakest (0.12), and insignificant. The incoming spillover effects are all significant, thereby indicating that all three types of firms benefit from the expansion of the meta-technology frontier. This spillover effect is again stronger for multi-output firms.

As undertaken previously for the efficiency and technology gap ratios, we discriminate firms with respect to their ownership status (Table 6) and technology intensity category (Table 7). This allows us to test whether our previous conclusions when grouping all firms remain true, and to propose more detailed results.

We find strong path dependences in efficiency for all ownership statuses. The mag-

Table 6. Path dependences and spillovers per ownership status

Ownership	Type	Present − Past			
		TGR *TGR*	*ER* *ER*	*TGR* *ER*	*ER* *TGR*
State	Multi	0.79 (0.00)	0.75 (0.00)	0.31 (0.00)	0.36 (0.00)
	Domestic	0.81 (0.00)	0.92 (0.00)	0.15 (0.08)	0.37 (0.00)
	Exporter	0.91 (0.00)	0.87 (0.00)	0.05 (0.00)	0.21 (0.00)
Private	Multi	0.62 (0.00)	0.65 (0.00)	0.58 (0.00)	0.39 (0.00)
	Domestic	0.69 (0.00)	0.71 (0.00)	0.35 (0.00)	0.35 (0.00)
	Exporter	0.70 (0.00)	0.81 (0.00)	0.21 (0.00)	0.31 (0.00)
Foreign	Multi	0.61 (0.00)	0.62 (0.00)	0.61 (0.00)	0.40 (0.00)
	Domestic	0.71 (0.00)	0.73 (0.00)	0.32 (0.00)	0.36 (0.00)
	Exporter	0.71 (0.00)	0.71 (0.00)	0.19 (0.05)	0.33 (0.00)
Collective	Multi	0.78 (0.00)	0.74 (0.00)	0.25 (0.00)	0.30 (0.00)
	Domestic	0.79 (0.00)	0.75 (0.00)	0.14 (0.12)	0.28 (0.00)
	Exporter	0.85 (0.00)	0.86 (0.00)	0.01 (0.41)	0.26 (0.00)

Table 7. Path dependences and spillovers per technology intensity category

Technology intensity	Type	Present − Past			
		TGR *TGR*	*ER* *ER*	*TGR* *ER*	*ER* *TGR*
Low	Multi	0.81 (0.00)	0.84 (0.00)	0.41 (0.00)	0.35 (0.00)
	Domestic	0.85 (0.00)	0.86 (0.00)	0.22 (0.00)	0.31 (0.00)
	Exporter	0.85 (0.00)	0.92 (0.00)	0.11 (0.15)	0.24 (0.05)
Medium-low	Multi	0.65 (0.00)	0.78 (0.00)	0.55 (0.00)	0.38 (0.00)
	Domestic	0.78 (0.00)	0.81 (0.00)	0.27 (0.00)	0.36 (0.00)
	Exporter	0.72 (0.00)	0.89 (0.00)	0.15 (0.08)	0.26 (0.03)
Medium-high	Multi	0.64 (0.00)	0.68 (0.00)	0.54 (0.00)	0.41 (0.00)
	Domestic	0.81 (0.00)	0.80 (0.00)	0.29 (0.00)	0.34 (0.00)
	Exporter	0.73 (0.00)	0.80 (0.00)	0.12 (0.05)	0.27 (0.00)
High	Multi	0.72 (0.00)	0.66 (0.00)	0.61 (0.00)	0.40 (0.00)
	Domestic	0.77 (0.00)	0.78 (0.00)	0.35 (0.00)	0.38 (0.00)
	Exporter	0.71 (0.00)	0.77 (0.00)	0.26 (0.02)	0.31 (0.00)

nitudes and signs of the Spearman correlation coefficients are comparable with those seen in Table 5, and are highly significant. First, for the efficiency ratios, the path dependence is weaker among multi-output firms for all ownership status, reminding us of the 'reshuffling' effect discussed earlier for Table 5. In addition, the private and foreign ownership statuses have smaller coefficients, indicating more internal adjustments in efficiency levels over time. Next, for the technology gap ratios, the path dependences are notably lower for multi-output firms and for private and foreign ownership status. These results suggest that these types of firms experience more technological progress over time.

Next, we also find evidence of spillovers in Table 6. Two distinct patterns emerge from that table. First, within each ownership status, the outgoing spillover effects are strongest from multi-output firms and weakest from export-only firms. This is consistent with the pattern observed in Table 5. Second, regardless of the output type, private- and foreign-owned firms generate more outgoing spillovers than do state- and collective-owned firms. In the latter cases, the Spearman correlation coefficients are both smaller and often insignificant. This finding reinforces the common observation that private- and foreign-owned firms are more productive (Berkowitz et al., 2017; Jefferson, Rawski, & Zhang, 2008), and supports the observation that foreign-owned firms constitute an important source of technology transfer (Cheung & Ping, 2004; Holmes, McGrattan, & Prescott, 2015). Finally, we find that the Spearman correlation coefficients are all highly significant for the incoming spillover effects. Judging by the size of these coefficients, private- and foreign-owned firms exhibit slightly stronger absorptive capacity. Except for the state ownership status, multi-output firms benefit the most from incoming spillovers and export-only firms benefit the least, but the differences are small.

Finally, we study path dependences and spillover effects by category of technology intensity in Table 7. In general, path dependence is strong and significant, regardless of output type and technology intensity category, yet the coefficients are notably lower for multi-output firms. This is reminiscent of the results observed in Tables 5 and 6. In addition, the Spearman correlation coefficients suggest that there is more efficiency improvement for high-tech firms and efficiency stagnancy for low-tech firms. We continue to see that multi-output firms generate the strongest outgoing spillover effects, while it is the opposite situation for export-only firms. High-tech firms have the highest coefficients, thereby confirming their leading role in generating technology spillovers. We also find that firms of all technology intensity categories benefit from incoming spillovers. Multi-output firms benefit the most and export-only firms benefit the least. Low-tech firms are found to benefit slightly less from incoming spillovers than the other types of firms.

3.3.3. Sensitivity tests[26]

As discussed before, while our estimation method is attractive because it does not require a functional form for the technology, it is generally sensitive to measurement errors and outliers. These two issues have been considered by using a robust estimation method. Here, we focus on two other potential problems that may directly affect the validity of our results.

First, our results may depend on the way we categorize the firms. In particular, because of the existence of marginal cases, it may be too extreme to define a domestic firm as a firm with no exports, and an export-oriented firm as a firm without domestic output. We wish to test whether and how relaxing these definitions may affect our results. Thus, we alternatively characterize a firm as domestic when its exports are no greater than 10% of the total output, and a firm as export oriented when its exports are no less than 90% of the total output. Firms that do not meet these criteria are defined as multi-output firms. We reproduce our main results and report them in Tables S7 and S8 of the supplementary material.

Second, our results may depend on the way we model the production process. A distinguishing feature of our modelling is to consider two different technologies for domestic outputs and exports. While we believe that this modelling is attractive (see our arguments in the introduction), it is not the common practice in the literature. Indeed, a common technology is more often assumed. In that case, the estimates of the efficiency and technology gap ratios are based on the aggregation output, while allocation of the inputs is ignored. The results using the common-technology assumption are provided in Tables S7 and S9 of the supplementary material.

Overall, our main conclusions continue to hold under these two alternative specifications. First, regardless of whether we use the alternative categorization of firms or the assumption of common technology, multi-output firms still exhibit the highest efficiency and technology gap ratios, while export-oriented firms present the poorest performance. Second, the Spearman correlation coefficients are all significant, and confirm that path dependence is weakest among multi-output firms, and both the outgoing and incoming spillover effects are the strongest among multi-output firms.[27] Overall, these sensitivity tests prove that our main conclusions are robust.

3.4. Discussion and policy implications

Chinese policymakers have long recognized the importance of promoting exports to boost economic growth. To achieve this aim, export-promotion programs–including VAT rebate, SEZs and financial convenience–have been designed to help Chinese firms compete in the international market. For this reason, studying the way in which exports have affected the performance of the manufacturing industry is of particular relevance in the case of China. In particular, this paper examines two dimensions of firm performance: efficiency level and technological advancement.

A particularity of our empirical approach is to partition firms with respect to their output orientation: domestic firms, export-only firms and multi-output firms. Technically, we bring greater realism to the analysis by recognizing that domestic outputs and exports potentially use different technologies. We find that multi-output firms not only define the technology frontier of the Chinese manufacturing industry, but also operate with higher efficiency. In contrast, export-only firms are the poorest performers. As a possible explanation for this result, we suspect that our definition of export-only firms mainly encompasses processing exporters, which have been found to be the least productive by other researchers (Dai et al., 2016). These results remain robust when we relax the definitions of the three types, adopt the simplified assumption of common technology and discriminate firms with respect to their ownership status and technology intensity category. Regarding the causes of the exceptional performance of multi-output firms and export-only firms, we find strong evidence of self-selection–that is, high-performance domestic firms self-select into the multi-output type, while low-performance domestic firms self-select into the export-only type. In contrast, we find little evidence that export firms (multi-output or export-only) obtain extra benefits from exporting once entry occurs. Finally, our findings reveal that private- and foreign-owned firms and high-tech firms have better performance.

A second aspect of our study is to investigate the presence of path dependences and spillovers in the Chinese manufacturing industry. We observe strong path dependences for the efficiency and technology gap ratios of firms. The level of path dependence is markedly lower for multi-output firms, and for private- and foreign-owned firms. This suggests that these firms have stronger technology advancements and more internal adjustments in efficiency levels. We observe strong outgoing spillovers from multi-output, private- and foreign-owned, and high-tech firms. This informs us that these firms are the main contributors of technology advancement in China's manufacturing industry. Finally, we observe significant incoming spillovers onto all types of firms. This indicates that all firms benefit from the technology advancement of the manufacturing industry as a whole. Multi-output, private- and foreign-owned, and high-tech firms usually benefit more, while low-tech firms benefit the least.

These findings have rich policy implications. First, because multi-output firms are generally more technologically advanced and more technically efficient, and because they generate substantial spillovers that benefit all firms, supporting multi-output firms is pivotal to China's future technology development. However, our results also reveal that export-only firms are the poorest performers and barely generate any spillovers to the industry. This contrasts the important promotion of these firms in China. Indeed, export-oriented firms have benefitted the most from the VAT rebate system and the input tariff rebate system. Overall, our findings suggest that Chinese policymakers should rethink their priorities in foreign trade. Although multi-output firms should be encouraged, policies in favour of dedicated exporters should be gradually removed.

Second, we find little support for the learning-by-doing hypothesis, yet strong evidence for the self-selection hypothesis. From the perspective of the policymaker, it is critical to facilitate high-performance firms to accomplish entry, rather than supporting and improving existing weak firms in the export market. Therefore, policies that reduce the entry barrier–such as government-sponsored foreign networks or financial convenience–will be more efficient than any type of rebate program provided to exiting exporters.

Third, our results contrast China's recent industrial reform strategy. Our results demonstrate that private- and foreign-owned firms take the lead in technical efficiency and technology advancement. Further, they generate more outgoing spillover effects. Thus, the industry continues to benefit from privatization and opening policies. Recently, however, a profound shift has been seen. The new industrial reform strategy is now described as 'the state advances as the private sector retreats'. Note that foreign-owned firms are not immune to this policy change. Thus, the strategy shift is doomed to harm the efficiency and technology advancement of China's manufacturing industry. In contrast, our results justify the leading role of high-tech industries in overall performance and in generating outgoing spillovers. Thus, these findings endorse China's dedication to developing high-tech industries, which is exemplified with a series of national policy outlines.[28]

Finally, the high levels of path dependences observed favour the need for policy interventions. State-owned domestic firms, state-owned export-only firms and low-tech export-only firms exhibit very high levels of path dependence, while their absorptive capacities of incoming spillovers are relatively weak. Strong path dependences imply efficiency and technology stagnancy, resulting in a vicious cycle that eventually prevents efficiency improvement or technology advancement. Hence, it is the role of policymakers to break the ice and revitalize these firms. Some existing measures are reported to be helpful, such as the 'grasp the large and let go of the small' initiative that was launched in the mid-1990s (Hsieh & Song, 2015). However, more work is required in this area.

4. Conclusion

China's strong manufacturing sector led the country to become the world's largest exporter in 2009. Various measures have been implemented at different levels to stimulate exports, with the rationale that exports generate multiple economic benefits, including efficiency and productivity gains. In this paper, we have investigated whether exports have been accompanied with the expected outcomes. In particular, we focused on two dimensions: efficiency and technological advancement, and the presence of spillovers and path dependence. The main distinguishing features of our empirical study were to recognize that different types of firms coexist in China, and that domestic products and exports potentially use different technologies. Moreover, we used a firm-level dataset and relied on a robust nonparametric estimation method.

Our results demonstrated the superiority of multi-output firms. Moreover, these firms generate strong outgoing spillovers to the industry. We also found that foreign- and private-owned firms and high-tech firms are the best performers. In contrast, export-only, state- and collective-owned, and low-tech firms were found to be the least efficient and least technologically advanced, and barely generate outgoing spillovers. Finally, we found evidence of strong path dependences and weak absorptive capacity for incoming spillovers for these firms.

On the basis of efficiency and technology improvement, our findings suggest that China should support multi-output firms and discourage export-oriented production. Policies should be designed to reduce barriers to the export market, rather than supporting inefficient firms in this market. Our results endorse the increasing attention devoted to developing high-tech firms, yet do not support the recent re-nationalization policy. Finally, we call for policy innovations that will break the stagnancy of high path dependence and low adsorption of incoming spillovers in some sectors.

Acknowledgements

The data file and the MATLAB program that replicates the analysis are available upon request.

Notes

[1]According to WTO (2016), over 70% of all exported merchandise is subject to a rebate rate between 15 and 17%. In 2015, China's VAT rebate totalled 1.29 trillion RMB, representing 17.5% of the total turnover tax revenue of the nation (China Financial Yearbook).

[2]In 2016, total merchandise exports from the 219 national SEZs reached 2.7 trillion RMB, or 19.5% of the national total. In the same year, total FDI in the SEZs was 330 billion RMB, or 39.4% of the national total (China Association of Development Zones).

[3]For example, the Export-Import Bank of China provides government concessional loans and preferential credit to exporters, and the China Export and Credit Insurance Corporation provides export credit insurance, reinsurance and credit guarantees. To provide an idea of the importance of these measures, in 2014, the Export-Import Bank of China disbursed 178.6 billion RMB in export sellers' credit and 59.4 billion RMB in export buyers' credit (WTO, 2016).

[4]The prevailing practice in the literature is to define firms with non-zero exports as exporters (Bernard & Jensen, 1995). Recent literature has documented the coexistence of firms of different product-orientation. Lu

(2010) reported a U-shaped distribution of export intensity among Chinese firms–that is, a large number of Chinese firms are either dedicated to domestic production or export production, yet many serve both markets. Lu et al. (2010) made a similar observation: firms that are dedicated to domestic production, export production and hybrid production are comparable in numbers among foreign affiliates. Our data indicate that the number of multi-output producers is about three times the number of export-only firms (Table S2 in the supplementary material).

[5]Yu, Ye, & Qu (2013) and Elliott & Zhou (2013) are two exceptions. Interestingly, Elliott & Zhou (2013) found that controlling for export status has a huge influence on the relative performance of state-owned firms.

[6]While previous studies recognize the importance of this distinction (Amiti & Freund, 2010; Jarreau & Poncet, 2012), few studies have related technology intensity to efficiency or technological advancement.

[7]A recent theoretical innovation was made by Bustos (2011), who modelled technology choice together with export choice. It was shown that only exporters adopt advanced technology. However, once the technology is chosen, firms produce exports and domestic merchandise using the same technology.

[8]Koopman et al. (2012); Ma, Wang, & Zhu (2015); and Upward et al. (2013) reported that a substantial fraction (about 50% in our period of study) of Chinese exporters participate in processing trade, and this type of trade uses a large amount of imported intermediate goods. Consequently, their average share of domestic value added is low (25.4%), while that of non-processing firms is nearly 90% (Koopman et al., 2012). The huge difference in input decomposition indicates that at least some exports are produced using a different technology.

[9]Our data indicate that 17.7% of all firms were foreign owned which generated 66.7% of total exports during the period of study.

[10]In microeconomic contexts, increasing attention has been devoted to the input-output linkages in efficiency analysis. See, for example, Cherchye, De Rock, & Walheer (2015, 2016); Ding, Dong, Liang, & Zhu (2017); Silva (2018); and Walheer (2018b,c, 2019c). The main motivation is to improve the realism and flexibility of modelling the production process. Recently, these techniques have also been used in macroeconomic contexts. See, for example, Walheer (2016a,b, 2018a, in press).

[11]The concept of meta-technology is based on the notion of meta-production function by Hayami & Ruttan (1970). See also Battese, Rao, & O'Donnell (2004), and O'Donnell et al. (2008) for more detail about this methodology.

[12]The validity of the chosen returns-to-scale assumption can be tested. We follow the technique discussed in Walheer (2019a) and find that constant returns-to-scale is acceptable for our empirical study. In addition, Equations (17) and (18) can easily be adapted to consider other returns-to-scale assumptions; in practice, it suffices to add constraints for the multipliers.

[13]Sector 42 (art ware and other manufacturing) is unclassified and is subsequently dropped from our analysis. Thus, we lose 37,808 observations, which is a small number compared with the size of the full sample (over 2.2 million).

[14]This occurs when registered capital is classified as legal person capital, which can be eventually owned by any entity. In the second step, ownership is well defined only if the registration information is clear about the control rights. Specifically, firms registered as state-owned enterprises, state-owned partnerships and state-owned limited liability companies are defined as state-owned; firms registered as collective enterprises and collective partnerships are defined as collective-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. All other registration types are left undefined.

[15]Greenaway, Guariglia, & Yu (2014); Walheer (2019b); and Wang & Wang (2015) recently highlighted the importance of foreign capital when studying Chinese firms. Unfortunately, the distinction between foreign and domestic capital is not available in the CIS dataset.

[16]We refer to the online appendix of Brandt et al. (2012) for more detail.

[17]We may think of factories and machines being used to produce both domestic outputs and exports, but the same employee cannot be used to produce both outputs simultaneously.

[18]For example, refer to Cherchye et al. (2016); Fukuyama & Weber (2008); and Sahoo, Mehdiloozad, & Tone (2014) for more discussion about considering quality in efficiency analysis. Interestingly, in the trade literature, the quality of an output is usually associated with or measured by its price (unit value). Examples include Bastos & Silva (2010); Bernard, Redding, & Schott (2011); and Hummels & Klenow (2005).

[19]The averages are computed by considering the relative importance of the firms. In practice, this is achieved by using the relative output shares as weights when computing the averages. This weighting scheme is also justified theoretically. Refer to Färe & Zelenyuk (2003) for the efficiency ratio, and Walheer (2018a) for the technology gap ratio.

[20]In Table 1, this is captured by $TGR = TGR^d$ and $ER = ER^d$ for domestic firms, and by $TGR = TGR^e$ and $ER = ER^e$ for export-only firms.

[21]Direct evidence usually comes from the customs data, which provide information on the nature of imported intermediates (processing or ordinary imports). Through using these data, one can isolate processing exporters from other exporters, as done, for example, by Dai et al. (2016). However, these data are unavailable in our case.

[22]A similar treatment has been used in, for example, Delgado, Fariñas, & Ruano (2002).

[23]There, the switchers are defined as domestic firms in 2003 that switch to export-only firms at some point between 2004 and 2007.

[24]*ER* is significant at the 10% significance level.

[25]Alternatively, the presence of path dependence and spillovers can be tested using (parametric) econometric methods. We refer to Tsekouras et al. (2016) for more detail about this approach.

[26]We thank the editor and an anonymous referee for suggesting these additional tests.

[27]The only exception occurs when we study path dependence of the technical efficiency ratio using the common-technology assumption (Table S9). There, we find that the coefficient of multi-output firms is slightly larger than that of domestic firms.

[28]These include the *Catalog of Industries, Products, and Technologies Currently Particularly Encouraged by the State* (2000) and the *Catalog for Guiding Industrial Restructuring* (2005, 2011 and 2013 editions), all developed by the National Development and Reform Commission.

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