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Independent R and D, Technology Introduction, and Green Growth in China's Manufacturing

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Abstract: An analysis of not only the effects of independent research and development (R and D), but also of the effects of the introduction of domestic and foreign technology on the growth of green manufacturing, can help China achieve the green transformation of manufacturing. In this paper we first use a non-directional distance function (NDDF) and meta-frontier methods to calculate a green growth index. Then, using 2003 to 2015 manufacturing panel data, we empirically test the effects of three different types of R and D investment on the green growth of China's manufacturing. The regression results show that there is significant industrial heterogeneity in the effects of independent R and D, in the introduction of domestic technology and in the introduction of foreign technology on the green growth of China's manufacturing. Independent R and D is conducive to the green growth of the three types of technological industries, but the contribution of independent R and D to green growth has gradually weakened with improvements in industrial technology. Domestic technology introduction is conducive to green growth in low and middle-technology industries, but its effect on high-technology industries is not significant. On the other hand, foreign technology introduction is conducive to the green growth of middle and high-technology industries, but its effect on low-technology industries is not significant.

Keywords: independent R and D; technology introduction; green growth; total-factor carbon productivity

1. Introduction

As the manufacturing sector is the principal driving force behind real economic growth in China, it follows that it is also responsible for the bulk of China's energy consumption and environmental pollution. In 2014, manufacturing accounted for 30.4% of GDP, but consumed 57.6% of total energy and emitted 70.5% of the total CO_2 [1]. It is, therefore, urgent for China's manufacturing sector to lay out a sustainable development path which not only promotes economic growth, but also protects the environment. This path is ultimately a green transformation road which is dominated by improving green total-factor productivity. In order to improve this green total-factor productivity, increases in research and development (R and D) investment are key.

Following the economic globalization of the last few years, R and D investment in China's manufacturing sector has mainly been of three types: independent R and D, domestic technology introduction, and foreign technology introduction. In reality, all kinds of activities related to green manufacturing can be precisely categorized within these three types. Eighteen major reports in China have clarified three kinds of independent R and D: original innovation, integrated innovation, and re-innovation after digestion and absorption. In view of this, we use the sum of internal R and D expenditure and the expenditure of digestion and absorption to represent independent R and D, and use expenditure on the introduction of foreign technology and expenditure on the purchase of domestic technology to represent foreign technology introduction and domestic technology introduction, respectively. It is pertinent to ask what the most effective kind of R and D investment is. What are the differences in the effects of independent R and D, domestic technology introduction and foreign technology introduction on the green growth of manufacturing? Is there an industrial heterogeneity in these effects? These will be the focus of this paper. In the context of China's current emphasis on independent innovation and green economy, the study has a strong practical significance for identifying those driving forces in the transformation of China's economic development structure and how to properly deal with the relationship between independent R and D and technological introduction in different manufacturing industries.

Endogenous growth theory indicates that R and D investment is the most important source of productivity growth. Quite a number of studies have conducted empirical tests on this issue and their results all show that R and D investment has a significant positive effect on productivity growth [2,3]. One drawback, however, is that the above studies use labor productivity to measure productivity. This cannot reasonably and accurately measure the effect of R and D investment on productivity growth mainly because the contribution of R and D investment to productivity growth is principally reflected in the growth of total-factor productivity (TFP) [4,5]. TFP refers to the increase in output resulting from technological progress, separated from the input of factors; in other words, the residual after eliminating the contribution of the input of factors. TFP is usually called the rate of technological progress, which is produced by technology progress. Compared to the labor productivity index, TFP is better at measuring technological progress. Nineteen major reports in China have explicitly proposed that China should promote sustainable and high-quality growth by the growth of TFP. Therefore, the use of TFP as a measure of productivity may, thus, be more appropriate. On this basis, many scholars have empirically analyzed the effect of R and D investment on the growth of TFP, and their results all show that R and D investment is conducive to the growth of TFP [6–8].

The above studies adopt, however, a single index to depict R and D investment, and do not consider the difference in the effects of different types of R and D investments on the growth of TFP [9]. Actually, as mentioned above, with the development of economic globalization, manufacturing R and D investment is mainly comprised of three types: independent R and D, domestic technology introduction and foreign technology introduction, and these different types of R and D investments have significant different influences on the growth of TFP [10]. New economic growth theory holds that independent R and D can create and accumulate knowledge, promote both products and technical progress, and process innovation, thereby providing a steady stream of motivation and support for sustainable economic growth [11]. Behind international trade theory is the notion that, through the introduction, digestion, and absorption of advanced technologies found in developed countries, developing countries can more quickly gain access to new international inventions, creativity, and technology, thereby obtaining the accelerating the economic growth that is needed for developing countries to realize both technological and economic catch up [12]. Another view, however, holds that, when directly introducing foreign technology, developed countries do not export their advanced technology to developing countries due to technology security concerns. In addition, most of the enterprises in developing countries usually digest and absorb advanced technology directly, which results in a lack of re-innovation capacity and serious technology dependence [13,14]. Therefore, some would say, the direct introduction of foreign technology may contribute very little to the growth of TFP.

Some scholars have empirically analyzed the effects of different R and D investment on the growth of TFP, but their conclusions differ. Based on a sample of China's large- and medium-sized manufacturing enterprises from 1995 to 1999, Hu et al. (2005) analyzed the effects of different R and D investment on the growth of TFP; the results showed that independent R and D and foreign technology introduction were both conducive to the growth of TFP, but the effect of domestic technology introduction was not. Based on regional industrial panel data in China from 1996 to

2003, Wu (2008) obtained the same conclusion. Li (2007) used the data envelopment analysis (DEA) method to measure the growth rate of TFP of China's 32 industrial sectors, and empirically analyzed the effects of these different types of R and D investments on the growth of TFP; the results showed that foreign technology introduction was indeed conducive to the growth of TFP, but the effects of independent R and D and domestic technology introduction were not significant [15]. Based on a sample of China's industrial panel data from 1999 to 2010, Wan and Zhu (2013) empirically tested the effects of different R and D investments on the growth of TFP; results showed that independent R and D and both domestic and foreign technology introduction were all conducive to the growth of TFP, but the role of domestic technology was relatively weak [16]. Based on the sample of China's industrial panel data from 2007 to 2011, Zhang et al. (2015) empirically analyzed the effects of different R and D investments on the growth of TFP; their results showed, however, that independent R and D, and both domestic and foreign technology introduction, were all conducive to the growth of TFP, with the role of independent R and D being relatively strong [17].

The existing literature has made great advances on the effects that R and D investment have on the growth of productivity, but there are still two areas for further study. On the one hand, the above literature has mainly analyzed the productivity growth effect of R and D investment from the perspective of TFP. Traditional TFP only considers production factors such as capital, labor, and desirable output, and does not incorporate energy and environmental factors into the measurement, thereby giving a bias to economic performance and social welfare [18,19]. In fact, R and D investment not only promotes the growth of productivity, but also saves energy and reduces pollutant emissions [20]. It is, thus, more appropriate to use green total-factor productivity to measure the productivity growth effect of R and D investment. It is noteworthy, however, that when analyzing the effects of R and D investment on the growth of productivity, the existing literature mostly ignores industrial heterogeneity [21]. Actually, due to significant differences between different manufacturing industries in their profitability, technical levels, industrial scales, energy consumption, and pollutant emissions, there is significant industrial heterogeneity in the effects of R and D investment on the green growth of China's manufacturing.

In view of the deficiencies of the above studies, this paper makes the following expansions: we use the non-directional distance function (NDDF) to construct a meta-frontier total-factor carbon productivity growth index, which not only considers situations in which desirable output and undesirable output change in different proportions, but also unifies the production technology frontier for subsequent measurement analysis. We further divide manufacturing into three categories: high-technology, middle-technology, and low-technology. Following this, we then empirically both analyze the effects of R and D investment on the green growth of China's manufacturing in industries of differing technology levels and highlight their differences.

2. Materials and Methods

2.1. The NDDF Measure for Determining the Green Growth Index

Assuming the production system has N decision-making units, each decision-making unit invests capital (K), labor (L), and energy (E), and produces desirable output (Y) and undesirable output (C) in the production process. According to the production theory of Färe et al. (2007) [22], in addition to meeting the closed set and bounded set, the production technology set T should also meet the strong disposability of inputs and desirable outputs, the joint and weak disposability, and the null-jointness of outputs. Assuming constant returns to scale, then the production technology set T can be specified as follows:

$$\begin{aligned} T = \{(K, L, E, Y, C) \colon & \sum_{n=1}^{N} \lambda_n K_n \leq K; \sum_{n=1}^{N} \lambda_n L_n \leq L; \sum_{n=1}^{N} \lambda_n E_n \leq E; \\ & \sum_{n=1}^{N} \lambda_n Y_n \geq Y; \sum_{n=1}^{N} \lambda_n C_n = C; \lambda_n \geq 0, n = 1, 2, \cdots N\} \end{aligned} \tag{1}$$

where λ_n denotes an intensity variable for constructing the production technology set. In order to measure the carbon emission performance of different decision units, we should define the directional distance function (DDF). The DDF contains two categories: the radial DDF and the radial DDF (NDDF). Compared to the radial DDF, the NDDF can more accurately identify the slacks of desirable output and undesirable output because it adopts more flexible slack variables. Based on Zhou et al. (2012) and Zhang et al. (2013) [23,24], we construct the following output-oriented NDDF:

$$\vec{D}(K,L,E,Y,C;g) = \sup\{\beta_Y + \beta_C : (K,L,E,Y+\beta_Y Y, C-\beta_C C) \in T\} \tag{2}$$

where $\beta = (\beta_Y, \beta_C)$ denotes a scale vector. $\beta = (\beta_Y, \beta_C) \neq 0$ means that the industry being considered has not optimized its outputs, and it has some potential for further improvement. Then we can easily obtain the potential expected output and potential unexpected output for the industry being evaluated. Based on Zhou et al. (2012), the total-factor carbon emission efficiency index (*TCEI*) can be defined as the ratio of potential target carbon intensity to actual carbon intensity:

$$TCEI = \frac{\text{Expected carbon intensity}}{\text{Actual carbon intensity}} = \frac{(C-\beta_C C)/(Y+\beta_Y Y)}{C/Y} = \frac{(1-\beta_C)}{(1+\beta_Y)} \tag{3}$$

The larger the *TCEI* is, the higher the carbon emission efficiency is. If *TCEI* = 1, it indicates that the decision unit is at the production frontier, that is, its carbon emission is efficient.

However, the above calculation of *TCEI* is based on the analysis of the same production technology frontier, and does not take the reality of a technological gap between different decision units into account. This approach puts those decision units which face different production technology frontiers into the same production technology frontier for comparison. It, thus, loses rationality and prevents us from accurately and reasonably measuring real carbon emission efficiency. In this paper we construct an improved NDDF based on consideration of the technology gap between different decision units, and calculate the meta-frontier total-factor carbon emission performance.

Three definitions of production technology sets are required for calculating and decomposing the meta-frontier total-factor carbon emission performance. First, we classify N decision units into H subgroups based on their production technologies. The subgroup h has N^h decision units and $\sum_{h=1}^{H} N^h = N$. The contemporaneous production technology set of group R_h can be defined as $T^C_{R_h} = \{(K^t, L^t, E^t, Y^t, C^t) : (K^t, L^t, E^t) \text{ can produce}(Y^t, C^t)\}$, where $t = 1, \cdots, T$. $T^C_{R_h}$ only contains all the observations of group R_h over the time period t. The inter-temporal production technology set of group R_h can be given by $T^I_{R_h} = T^1_{R_h} \cup T^2_{R_h} \cup \cdots \cup T^T_{R_h}$. This set contains all the observations of group R_h at all times. The global production technology set can be defined as $T^G = T^I_{R_1} \cup T^I_{R_2} \cup \cdots \cup T^I_{R_H}$. This set contains all the observations for all groups at all times.

As a result, the NDDF described in Equation (2) can be expressed in terms of these three types of production technologies. The contemporaneous NDDF can be obtained from: $\vec{D}^C(\cdot) = \sup\{\beta^C_Y + \beta^C_C : (K,L,E,Y+\beta^C_Y Y, C-\beta^C_C C) \in T^C_{R_h}\}$. The group NDDF can be obtained from: $\vec{D}^I(\cdot) = \sup\{\beta^I_Y + \beta^I_C : (K,L,E,Y+\beta^I_Y Y, C-\beta^I_C C) \in T^I_{R_h}\}$. The global NDDF can be obtained from: $\vec{D}^G(\cdot) = \sup\{\beta^G_Y + \beta^G_C : (K,L,E,Y+\beta^G_Y Y, C-\beta^G_C C) \in T^G\}$. By solving these NDDFs, we can obtain the following six associated values of *TCEI*:

$$TCEI^d(K^S, L^S, E^S, Y^S, C^S) = \left(\frac{1-\beta^d_C}{1+\beta^d_Y}\right)^S \tag{4}$$

where $S = t, t+1$, and $d \equiv (C, I, G)$. However, these total-factor carbon emission efficiencies only measure the static carbon emission performance, and do not measure the dynamic changes of carbon emission performance. Based on Oh (2010) [25] and Zhang and Choi (2013), we develop the meta-frontier total-factor carbon emission performance index (MTCPI) to analyze the dynamic changes in carbon emission performance, and then further decompose it.

$$\begin{aligned}
MTCPI &= \frac{TCEI^{G}(.^{t+1})}{TCEI^{G}(.^{t})} \\
&= \left[\frac{TCEI^{C}(.^{t+1})}{TCEI^{C}(.^{t})}\right] \times \left[\frac{\frac{TCEI^{I}(.^{t+1})}{TCEI^{C}(.^{t+1})}}{\frac{TCEI^{I}(.^{t})}{TCEI^{C}(.^{t})}}\right] \times \left[\frac{\frac{TCEI^{G}(.^{t+1})}{TCEI^{I}(.^{t+1})}}{\frac{TCEI^{G}(.^{t})}{TCEI^{I}(.^{t})}}\right] \\
&= \left\{\frac{\left(\frac{1-\beta_{C}^{C}}{1+\beta_{Y}^{C}}\right)^{t+1}}{\left(\frac{1-\beta_{C}^{C}}{1+\beta_{Y}^{C}}\right)^{t}}\right\} \times \left\{\frac{\frac{\left(\frac{1-\beta_{C}^{I}}{1+\beta_{Y}^{I}}\right)^{t+1}}{\left(\frac{1-\beta_{C}^{C}}{1+\beta_{Y}^{C}}\right)^{t+1}}}{\frac{\left(\frac{1-\beta_{C}^{I}}{1+\beta_{Y}^{I}}\right)^{t}}{\left(\frac{1-\beta_{C}^{C}}{1+\beta_{Y}^{C}}\right)^{t}}}\right\} \times \left\{\frac{\frac{\left(\frac{1-\beta_{C}^{G}}{1+\beta_{Y}^{G}}\right)^{t+1}}{\left(\frac{1-\beta_{C}^{I}}{1+\beta_{Y}^{I}}\right)^{t+1}}}{\frac{\left(\frac{1-\beta_{C}^{G}}{1+\beta_{Y}^{G}}\right)^{t}}{\left(\frac{1-\beta_{C}^{I}}{1+\beta_{Y}^{I}}\right)^{t}}}\right\} \\
&= EC \times BPC \times TGC
\end{aligned} \tag{5}$$

In Equation (5), $MTCPI$ denotes the meta-frontier total–factor carbon productivity growth index, and reflects the green growth effect. If $MTCPI > 1$, it indicates positive green growth. The greater the $MTCPI$, the faster green growth is. EC denotes the carbon emission technological efficiency change index. If $EC > 1$, it indicates that the output level is closer to the contemporaneous best production frontier, implying an efficiency improvement. BPC denotes the best practice gap change index, and reflects the technical progress degree. If $BPC > 1$, it indicates that the contemporaneous frontier is moving forward to the inter-temporal frontier, implying technical progress. TGC denotes the technological gap change index, and reflects the technological catch-up degree. If $TGC > 1$, it indicates a decrease in the technological gap between the meta-frontier and the group-frontier, implying technological catch-up.

2.2. Dynamic Panel Model

According to the Cobb-Douglas production function, we regard the knowledge and technology acquired from R and D activities as an important production factor, so the relationship between factor inputs and output in the production process can be expressed as:

$$Y_{it} = Ae^{\lambda t} I_{it}^{\alpha} L_{it}^{\beta} K_{it}^{\gamma} \tag{6}$$

where Y_{it} denotes the output of industry i in t year, K_{it} denotes the physical capital stock, L_{it} denotes the labor input, and I_{it} denotes the knowledge capital stock. Unlike tangible factors K_{it} and L_{it}, the knowledge capital stock I_{it} cannot be directly measured because it involves more intangible assets, but it is mostly generated from R and D activities [9]. We, thus, further decompose I_{it} into three parts: the capital stock of independent R and D (*IR*), the capital stock of domestic technology introduction (*ID*), and the capital stock of foreign technology introduction (*IF*) [10,16]. The above Cobb-Douglas production function can then be extended as follows:

$$Y_{it} = Ae^{\lambda t} IR_{it}^{\alpha_1} ID_{it}^{\alpha_2} IF_{it}^{\alpha_3} L_{it}^{\beta} K_{it}^{\gamma} \tag{7}$$

Then the total-factor productivity (*TFP*) can be expressed as follows:

$$TFP_{it} = Y_{it}/L_{it}^{\beta} K_{it}^{\gamma} = Ae^{\lambda t} IR_{it}^{\alpha_1} ID_{it}^{\alpha_2} IF_{it}^{\alpha_3} \tag{8}$$

After taking the logarithm on both sides of Equation (8), we then take the time derivative, and obtain the following equation:

$$\rho_{it} = \frac{d(TFP_{it})/dt}{TFP_{it}} = \lambda + \alpha_1 \frac{d(IR_{it})/dt}{IR_{it}} + \alpha_2 \frac{d(ID_{it})/dt}{ID_{it}} + \alpha_3 \frac{d(IF_{it})/dt}{IF_{it}} \tag{9}$$

where ρ_{it} denotes the annual rate of change of TFP, α_1, α_2, and α_3 denote the output elasticity of these three types of R and D investments. According to the definition of output elasticity in Microeconomics, we can obtain that $\alpha_1 = \frac{\partial Y_{it}}{\partial IR_{it}} \cdot \frac{IR_{it}}{Y_{it}}$, $\alpha_2 = \frac{\partial Y_{it}}{\partial ID_{it}} \cdot \frac{ID_{it}}{Y_{it}}$, $\alpha_3 = \frac{\partial Y_{it}}{\partial IF_{it}} \cdot \frac{IF_{it}}{Y_{it}}$. Therefore, Equation (9) can also be expressed as follows:

$$\rho_{it} = \lambda + \phi_1 \frac{d(IR_{it})/dt}{Y_{it}} + \phi_2 \frac{d(ID_{it})/dt}{Y_{it}} + \phi_3 \frac{d(IF_{it})/dt}{Y_{it}} \tag{10}$$

where $\phi_1 = \partial Y_{it}/\partial IR_{it}$, $\phi_2 = \partial Y_{it}/\partial ID_{it}$, $\phi_3 = \partial Y_{it}/\partial IF_{it}$, and these three variables denote the marginal output of independent R and D, domestic technology introduction, and foreign technology introduction, respectively. $d(IR_{it})/dt$, $d(ID_{it})/dt$, $d(IF_{it})/dt$ denote the rate of change of capital stock of these three types of R and D investments, respectively.

In general, it is difficult to directly measure the rate of change of R and D capital stock because it is not only related to annual R and D investment, but also related to the depreciation and lagged effect of the original R and D capital stock. Based on Sun et al. (2016), considering the faster growth of R and D investment, we can approximately regard the depreciation of R and D capital stock as zero, and ignore its lag effect. Then the change of R and D capital stock in t year is equal to its amount of investment. Equation (10) can thus also be expressed as follows:

$$\rho_{it} = \lambda + \phi_1 \frac{VR_{it}}{Y_{it}} + \phi_2 \frac{VD_{it}}{Y_{it}} + \phi_3 \frac{VF_{it}}{Y_{it}} \tag{11}$$

where VR_{it}, VD_{it}, and VF_{it} denote the amount of investment in independent R and D, domestic technology introduction, and foreign technology introduction, respectively. The ratio to Y_{it} denotes the investment intensity of these three types of R and D investments.

To interpret growth of TFP, in addition to the three types of R and D investments, we add some control variables, including environmental regulation (ER), marketization level (MS), and foreign direct investment (FDI). Environmental regulation has important effects on the growth of TFP. On the one hand, it can increase the cost burden of enterprises, impose new constraints on their production behavior, and make their production, management, and sales more difficult, all of which are not conducive to the growth of TFP [26]. On the other hand, environmental regulation can stimulate enterprises to develop technological innovation, make energy saving and emission reductions, improve their management efficiency and optimize their resource allocation; these are conducive to the growth of TFP [27]. Market level is an important factor affecting the growth of TFP. Generally speaking, the higher the market level is, the more significant the spillover effect of innovation is and the higher the resource allocation efficiency is; all are conducive to the growth of TFP [16]. Foreign direct investment also has important effects on the growth of TFP because it can promote improvements in technical levels and energy efficiency through demonstration effects, competition effects, and technology spillover effects. We, thus, expect that FDI can promote the growth of TFP [28]. In view of the foregoing, we construct the following basic econometric model:

$$\begin{aligned} \ln \rho_{it} &= \lambda + \phi_1 \ln R_{it} + \phi_2 \ln D_{it} + \phi_3 \ln F_{it} \\ &+ \phi_4 \ln ER_{it} + \phi_5 \ln MS_{it} + \phi_6 \ln FDI_{it} + \varepsilon_{it} \end{aligned} \tag{12}$$

where R_{it}, D_{it}, and F_{it} denote the investment intensity of the three types of R and D investment, respectively, and ε_{it} denotes random error term. On this basis, we incorporate the lag effect of the growth of TFP, and establish the following dynamic panel model:

$$\begin{aligned} \ln \rho_{it} &= \tau \ln \rho_{i(t-1)} + \lambda + \phi_1 \ln R_{it} + \phi_2 \ln D_{it} + \phi_3 \ln F_{it} \\ &+ \phi_4 \ln ER_{it} + \phi_5 \ln MS_{it} + \phi_6 \ln FDI_{it} + \varepsilon_{it} \end{aligned} \tag{13}$$

where τ denotes the regression coefficient of first-order lag of the rate of change of TFP, and reflects the effect of previous related factors on this period.

2.3. Variable Descriptions and Data Sources

Due to a major adjustment in China's national economic classification system in 2002, we have selected statistics on China's manufacturing industries only from 2003 to 2015 for analysis. Furthermore, since the statistical caliber of China's manufacturing industries changed to some extent in 2011, we needed to deal with some industries before 2011 and some after 2011. We, thus, combined the rubber industry and the plastics industry into the rubber and plastics industry, and combined the automobile manufacturing and railway, ship, aerospace, and other transportation equipment manufacturing into transportation equipment manufacturing. Since the output of the waste resources and waste materials recycling and processing industry was too small, and its data was incomplete, it was not included for consideration. We, thus, selected 28 manufacturing industries for analysis (See Table A1 for more details). The data in the paper are from the China Statistical Yearbook, the China Industry Statistical Yearbook, the China Statistical Yearbook on Science and Technology, the China Energy Statistical Yearbook and the China Environmental Statistical Yearbook, from 2004 to 2016. The following is the detailed description of each variable.

For the calculation of the rate of TFP growth, we use the $MTCPI$ in Section 3.1. Its calculation involves the selection of input and output variables and the following is a detailed description of each input and output variable: (1) Input variables. With respect to the input index, we use three variables: capital, labor, and energy. Capital is represented by the amount of capital stock of each industry. We use the perpetual inventory method to estimate capital stock, deflated by the fixed asset investment price indices in 2003. We use the average number of industrial workers and energy consumption to measure labor and energy, respectively. (2) Desirable output variable: desirable output is derived from the main business income of large and medium-sized industrial enterprises deflated by 2003 GDP price indices. (3) Undesirable output variable: We use the method of calculation provided by the IPCC (2007) to calculate carbon emissions [29]. In the selection of fossil energy types and carbon emission coefficients, we refer to the approach of Cheng et al. (2018) [30].

For the core explanatory variables, we use the ratio of independent R and D investment, domestic technology introduction investment and foreign technology introduction investment to main business income to measure R_{it}, D_{it}, and F_{it}, respectively. For the selection of control variables, we use the ratio of industrial waste water and waste gas pollution control costs to main business income to measure environmental regulation (ER). We use the ratio of the number of employees of non-state-owned economic units to the total number of employees to measure the marketization level (MS). We use the ratio of the main business income of foreign enterprises to the main business income of large- and medium-sized industrial enterprises to measure foreign direct investment (FDI). We expect the above control variables to have significant positive effects on the growth of green manufacturing.

3. Results

3.1. The MTCPI and Its Decomposition

According to the industry classification criteria of the European Union Statistical Bureau, we divide manufacturing industries into low-technology industries, middle-technology industries, and high-technology industries according to their technology level (see classification in Appendix A for more details). We then calculate the MTCPI and its decomposition into 28 manufacturing industries from 2003 to 2015, with the whole calculation and decomposition process realized through MATLAB 2016b (MathWorks: Natick, MA, USA).

As can be seen from Table 1, the average MTCPI of China's manufacturing is 1.0052, and the MTCPI of 21 manufacturing industries is greater than 1, indicating that, to some extent, China's manufacturing realized overall green growth from 2003 to 2015. However, the average MTCPI of China's manufacturing is slightly larger than 1, and the MTCPI of seven manufacturing industries is smaller than 1, indicating that green growth is very slow; there is still a long road for China's manufacturing to realize green transformation. From the decomposition of MTCPI, we see that the green growth of China's manufacturing is mainly driven by technical progress, while the deterioration in technological efficiency and the expansion of the technology gap have, to a certain extent, jointly inhibited green growth.

Table 1. The MTCPI and its decomposition in 2003–2015.

Industrial ID	Subgroup	MTCPI	EC	BPC	TGC
13	I	0.9888	0.9495	1.0000	1.0413
14	I	1.0005	0.9823	1.0208	0.9977
15	I	1.0023	0.9874	1.0169	0.9982
16	I	1.0439	1.0000	1.0387	1.0050
17	I	0.9998	0.9805	1.0210	0.9987
18	I	0.9784	0.9727	1.0115	0.9945
19	I	0.9630	0.9696	1.0017	0.9916
20	I	1.0028	0.9915	1.0163	0.9952
21	I	1.0044	0.9862	1.0260	0.9926
22	I	1.0006	0.9937	1.0071	0.9999
23	I	1.0081	0.9841	1.0395	0.9854
24	I	1.0294	1.0059	1.0193	1.0040
40	I	0.9721	0.9474	1.0000	1.0260
25	II	0.9982	1.0000	1.0035	0.9947
26	II	1.0005	0.9991	1.0220	0.9799
28	II	1.0026	1.0000	1.0393	0.9647
29	II	1.0016	1.0000	1.0068	0.9948
30	II	1.0003	1.0059	1.0057	0.9888
31	II	1.0002	1.0085	1.0230	0.9695
32	II	1.0006	1.0000	1.0258	0.9754
33	II	0.9974	1.0000	0.9986	0.9988
34	II	1.0034	1.0000	1.0115	0.9920
35	II	1.0090	1.0000	1.0141	0.9949
27	III	1.0031	1.0551	1.0033	0.9476
36	III	1.0180	1.0236	1.0280	0.9674
37	III	1.0964	0.9853	1.0229	1.0879
38	III	1.0163	1.0000	1.0163	1.0000
39	III	1.0131	0.9852	1.0260	1.0022
Group I		0.9996	0.9808	1.0168	1.0023
Group II		1.0014	1.0013	1.0150	0.9854
Group III		1.0294	1.0098	1.0193	1.0010
The whole Group		1.0052	0.9933	1.0166	0.9960

During the study period, the MTCPI of the electrical equipment and machinery manufacturing industry is the greatest, indicating that its green growth is the most rapid. In terms of its decomposition, although the deterioration in technological efficiency has inhibited green growth, both technical progress and a decrease in the technological gap have promoted it, with the decrease in the technological gap playing a major promoting role. The MTCPI of leather, furs, feathers (down), and related product manufacturing is the smallest, indicating that its negative green growth is the fastest. In terms of decomposition, although technical progress is conducive to green growth, the deterioration in technological efficiency and the expansion of the technological gap have jointly inhibited green growth, with the deterioration in the technological efficiency playing a major inhibiting role.

In the study period, improvements in technological efficiency are conducive to green growth in five industries, with the promoting effect on the medical and pharmaceutical products manufacturing industry being the strongest. The deterioration in technological efficiency has, however, inhibited green growth in 14 industries, with the inhibiting effect on the handicrafts and other manufacturing industry being the strongest. Technical progress is conducive to the green growth of 25 industries, with the promoting effect on chemical and fiber manufacturing being the strongest. Technical regress, by contrast, has only inhibited green growth in the metal products industry. A decrease in the technology gap is conducive to the green growth of six industries, with the promoting effect on the electrical equipment and machinery manufacturing industry being the strongest. The expansion of technology gap has inhibited the green growth of 21 industries, with the inhibiting effect on the medical and pharmaceutical products manufacturing the strongest. We, thus, find that technical progress is the main driving force for the green growth of China's manufacturing industries, while deterioration in technological efficiency and an expansion of the technology gap have jointly inhibited that growth to a certain extent.

There is significant difference between each subgroup in the MTCPI. The green growth of high-technology industries is the fastest, followed by that of middle-technology industries; low-technology industries have negative green growth. With respect to the low-technology industries, and in terms of decomposition, although technical progress and the decrease of the technological gap are conducive to green growth, it is the deterioration in technological efficiency that has inhibited that green growth to a large extent. For middle-technology industries, although the expansion of the technological gap has inhibited green growth, improvements in technological efficiency and technical progress have jointly promoted it. With respect to the high-technology industries, improvement in technological efficiency, technical progress, and the decrease in the technological gap have jointly promoted green growth, with technical progress playing the primary promoting role.

After comparing the decomposition of each subgroup, we find that an improvement in technological efficiency is conducive to the green growth of middle- and high-technology industries, with a promoting effect on high-technology industries being the stronger of the two. The deterioration in technological efficiency has inhibited the green growth of low-technology industries. Technical progress is conducive to the green growth of all three industries, with the promoting effect on high technology industry being the strongest, followed by low-technology industries, and middle-technology industries the weakest. The decrease in technological gap is conducive to the green growth of low and high-technology industries, where the promoting effect on low-technology industries is stronger. The expansion of the technological gap, on the other hand, has inhibited green growth in middle-technology industries.

3.2. Regression Results

There are two main methods for estimating the dynamic panel model: the difference generalized moment estimation method (difference GMM) and the system generalized moment estimation method (system GMM). Since the difference GMM has the problem of weak instrumental variables in the estimation process, there may be serious finite sample bias. The system GMM can make full use of sample information, so the finite sample bias can be significantly reduced. In addition, it can also effectively solve the problem of variable endogeneity. Therefore, we use the system GMM to estimate the dynamic panel model (13), and the results are shown in Table 2.

Table 2. The estimation results of dynamic panel model.

Variable	Low Technology				Middle Technology				High Technology			
	MTCPI	**EC**	**BPC**	**TGC**	**MTCPI**	**EC**	**BPC**	**TGC**	**MTCPI**	**EC**	**BPC**	**TGC**
τ	0.127 *** [4.27]	0.204 *** [5.28]	0.257 *** [6.83]	0.158 *** [4.96]	0.131 *** [5.12]	0.216 *** [5.59]	0.238 *** [7.51]	0.139 *** [3.49]	0.133 *** [5.36]	0.223 *** [6.81]	0.229 *** [7.12]	0.145 *** [4.23]
$\ln R$	0.281 *** [4.06]	0.320 [0.53]	0.194 *** [5.61]	0.076 *** [3.84]	0.213 *** [2.79]	0.072 *** [4.26]	0.155 * [1.76]	0.205 [0.84]	0.076 * [1.80]	0.145 [0.97]	0.052 ** [2.01]	0.095 [0.57]
$\ln D$	0.083 * [1.72]	0.066 [0.56]	0.178 *** [4.63]	0.087 ** [2.04]	0.169 *** [3.58]	0.204 [0.67]	0.085 *** [4.14]	0.147 *** [2.95]	0.137 [0.62]	−0.145 [−0.68]	0.052 [1.25]	0.062 [0.93]
$\ln F$	0.092 [1.16]	−0.126 [−0.85]	0.052 [1.01]	−0.095 [−0.64]	0.153 ** [2. 09]	0.132 [4.26]	0.067 * [1.81]	0.166 *** [3.26]	0.196 *** [4.96]	0.137 [0.80]	0.094 *** [3.25]	0.176 *** [4.91]
$\ln ER$	0.016 [0.73]	0.003 [0.21]	0.004 *** [2.79]	0.005 [0.54]	0.037 *** [8.547]	0.029 ** [3.26]	0.006 * [1.76]	0.048 [0.97]	0.005 [7.784]	0.017 [0.14]	0.008 [0.35]	0.026 [1.27]
$\ln MS$	0.029 ** [2.08]	0.009 *** [2.77]	0.033 * [1.75]	0.002 [0.76]	0.012 * [1.83]	0.021 *** [2.75]	0.006 * [1.80]	0.001 [0.84]	0.004 [0.73]	0.010 [0.85]	0.005 [0.76]	0.006 [0.78]
$\ln FDI$	0.007 [0.55]	0.019 [0.72]	0.008 [1.02]	0.010 [0.71]	−0.021 [−0.76]	0.013 [0.83]	−0.009 [−1.05]	−0.016 [−0.79]	0.026 [1.14]	0.024 [1.28]	0.025 [1.06]	0.024 [1.37]
cons	−1.045 *** [−2.78]	−0.894 ** [−2.05]	−0.876 *** [−2.89]	−0.986 *** [−2.73]	−0.682 * [−1.73]	0.710 *** [−3.84]	−0.641 * [−1.81]	−0.690 *** [−2.75]	0.903 *** [3.17]	0.829 *** [3.74]	0.873 *** [3.36]	0.952 *** [3.93]
AR(1)	(0.014)	(0.004)	(0.009)	(0.022)	(0.018)	(0.007)	(0.006)	(0.028)	(0.020)	(0.005)	(0.010)	(0.025)
AR(2)	(0.153)	(0.079)	(0.108)	(0.253)	(0.172)	(0.094)	(0.089)	(0.292)	(0.191)	(0.082)	(0.113)	(0.247)
Hansen Test	(0.998)	(1.000)	(0.999)	(1.000)	(0.999)	(0.999)	(0.998)	(1.000)	(0.998)	(1.000)	(0.999)	(0.999)

Figures in parentheses are t values. *, **, *** denote statistical significance levels at 10%, 5%, and 1%, respectively.

As can be seen from the diagnostic tests, we find that the results of AR(1) and AR(2) show that there is first-order serial correlation and no second-order serial correlation for the first-differenced residuals, indicating that the system GMM estimator is consistent. In addition, the results of the Hansen test also show that the selected instrumental variables are rational and effective. In the regression results, the regression coefficients of the first-order lag of the dependent variable are positive at the 1% significance level, indicating that the green growth index has a significant dynamic effect. This is mainly because manufacturing development is a continuous and dynamic economic system, its previous preparation and accumulation can be manifested by the technical level, knowledge, human capital, and market scale, all of which can affect manufacturing development in both the current and subsequent periods.

4. Discussion

We first analyze the effects of independent R and D on the green growth of different technology-level industries. From Table 2 we find that independent R and D is significant and conducive to the green growth of the three types of technology-level industries, but the contribution of independent R and D to green growth has gradually been weakened with improvements in industrial technology levels. Furthermore, there are significant differences in the way in which independent R and D promotes the green growth of different technology-level industries. With respect to the low-technology industries, independent R and D has promoted green growth mainly by promoting technical progress and narrowing the technological gap. With respect to the middle-technology industries, independent R and D has promoted green growth mainly by promoting technical progress and improving technological efficiency. With respect to the high-technology industries, independent R and D has promoted green growth mainly by promoting technical progress.

We then analyze the effects of the introduction of domestic technology on the green growth of different technology-level industries. From Table 2 we find that the introduction of domestic technology is significantly conducive to the green growth of low- and middle-technology industries, with the promoting effect on low-technology industry being stronger. The contribution of the introduction of domestic technology to the green growth of high-technology industries is not significant. In addition, there are significant differences in the ways in which domestic technology introduction promotes the green growth of different technology-level industries. With respect to low- and middle-technology industries, domestic technology introduction has promoted their green growth mainly by promoting technical progress and narrowing the technological gap. With respect to the high-technology industries, the effects of domestic technology introduction on technological efficiency, technical progress, and the technological gap are not significant.

We then analyze the effects of the introduction of foreign technology on the green growth of different technology-level industries. From Table 2 we find that foreign technology introduction is significantly conducive to the green growth of middle- and high-technology industries, with the promoting effect on high-technology industries being stronger. The contribution of foreign technology introduction to the green growth of low-technology industries is not significant. Furthermore, there are significant differences in the way in which foreign technology introduction promotes the green growth of different technology-level industries. With respect to the middle- and high-technology industries, foreign technology introduction has promoted their green growth mainly by promoting technical progress and narrowing the technological gap. With respect to low-technology industries, the effects of foreign technology introduction on technological efficiency, technical progress, and the technological gap are not significant.

We then analyze the effects of different types of R and D investment on green growth. From Table 2 we find that, with respect to low-technology industries, independent R and D and domestic technology introduction are conducive to its green growth, with independent R and D playing the primary promoting role. The effect of foreign technology introduction is not significant. With respect to middle-technology industries, independent R and D, domestic technology introduction and foreign technology introduction are all conducive to its green growth, with the promoting role of independent R and D being the strongest. This is followed by domestic technology introduction with foreign technology introduction making the weakest contribution. With respect to high-technology industries, independent R and D and foreign technology introduction are conducive to green growth, with foreign technology introduction playing a significant promoting role. The effect of domestic technology introduction is not significant.

Finally, we analyze the effects of control variables on the green growth of different technology-level industries. As can be seen from Table 2, environmental regulation is only conducive to the green growth of middle-technology industries, while its effects on the low- and high-technology industries are not significant. This is mainly because the middle technology industries are comprised more of resource-intensive and energy-intensive industries. Environmental regulation can force and stimulate enterprises to engage in technological innovation, improve energy efficiency, and reduce pollutant emissions, which are all conducive to green growth. The marketization level is conducive to the green growth of low and high-technology industries, while its effect on high-technology industries is not significant. This is mainly because high-technology industries are composed of more state-owned large- and medium-sized enterprises, with large degrees of monopoly at play. This inhibits the market from exerting a larger promoting role. The effect of foreign direct investment on the green growth of different technology-level industries is not significant. This is mainly because the structure of FDI in Chinese manufacturing is still dominated by resource-intensive and labor-intensive industries and, thus, does not bring significant knowledge and technology spillovers.

5. Conclusions

Based on the meta-frontier and total-factor analysis framework, we measure the green growth index of 28 manufacturing industries from 2003 to 2015, and then use a dynamic panel model to empirically analyze the effects of different types of R and D investments on green growth in manufacturing. The results show that the green growth index has significant group heterogeneity, that is, the green growth in high-technology industries is the fastest, followed by middle-technology industries, with low-technology industries having negative green growth. There is also significant industrial heterogeneity in the effects of both independent R and D and the introduction of both domestic and foreign technology introduction on the growth of green manufacturing. In light of the above conclusions, the main enlightenments are as follows:

(1) China should improve the current ways it conducts scientific and technological activities, and should create a favorable external environment for independent R and D in enterprises. China should strengthen the protection of intellectual property, increase R and D funding, vigorously develop venture capital and incubators, stimulate enterprises to engage in more R and D activities through science and technology investment and financing policies, and accelerate the transformation and application of technological innovation. We should also vigorously improve original innovation capacity, key technological innovation capacity, and system integration capacity based on independent R and D. (2) While encouraging enterprises to increase R and D investment, the low and middle-technology industries can introduce appropriate advanced domestic technology. High-technology industries should more actively promote the introduction and use of advanced foreign technology. We should actively study and draw on domestic and foreign advanced technology, and make full use of global scientific and technological resources to speed up our own development. Meanwhile, when introducing domestic and foreign advanced technology, China should focus on independent R and D and its digesting and absorbing capacities, avoid the passive situation of "introduction-imitation-reintroduction-re-imitation", and gradually eliminate the path dependence of technology introduction.

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Appendix A

Table A1. Manufacturing code and classification.

Industry Classification	Industry Code	Industry
Subgroup I: The low-technology industries	13	Agricultural and food processing
	14	Food production
	15	Beverage production
	16	Tobacco processing
	17	Textile industry
	18	Textile clothing, shoes, and hat products
	19	Leather, furs, feathers (down), and related products
	20	Timber processing, bamboo, cane, palm fiber, and straw products
	21	Furniture manufacturing
	22	Papermaking and paper products
	23	Printing and record medium reproduction
	24	Cultural, educational, and sports goods
	40	Handicrafts and other manufacturing
Subgroup II: The middle-technology industries	25	Petroleum processing, coking, and nuclear fuel processing
	26	Chemical raw materials and chemical products manufacturing
	28	Chemical and fiber manufacturing
	29	Rubber and plastic products
	30	Nonmetal mineral products
	31	Smelting and pressing of ferrous metals
	32	Smelting and pressing of nonferrous metals
	33	Metal products
	34	General equipment
	35	Special equipment
Subgroup III: The high-technology industries	27	Medical and pharmaceutical products
	36	Transportation equipment
	37	Electrical equipment and machinery
	38	Telecommunications, computers and other electronic equipment
	39	Instruments, meters, and cultural and clerical machinery

References

1. Yao, X.; Guo, C.W.; Shao, S.; Jiang, Z.J. Total-factor CO_2 emission performance of China's provincial industrial sector: A meta-frontier non-radial Malmquist index approach. *Appl. Energy* **2016**, *184*, 1142–1153. [CrossRef]
2. Doraszelski, U.; Jaumandreu, J. R&D and Productivity: Estimating endogenous productivity. *Rev. Econ. Stud.* **2013**, *80*, 1338–1383.
3. Hlku, H.; Pamukcu, M.T. The impact of R&D and knowledge diffusion on the productivity of manufacturing firms in Turkey. *J. Product. Anal.* **2015**, *44*, 79–95.
4. Medda, G.; Piga, A.C. Technological spillovers and productivity in Italian manufacturing firms. *J. Product. Anal.* **2014**, *41*, 419–434. [CrossRef]
5. Harris, R.; Moffat, J. Plant-level determinants of total factor productivity in Great Britain, 1997–2008. *J. Product. Anal.* **2015**, *44*, 1–20. [CrossRef]
6. Kancs, D.; Siliverstovs, B. R&D and non-linear productivity growth. *Res. Policy* **2016**, *45*, 634–646.

7. Ugur, M.; Trushin, E.; Solomon, E.; Guidi, F. R&D and productivity in OECD firms and industries: A hierarchical meta-regression analysis. *Res. Policy* **2016**, *45*, 2069–2086.
8. Bengoa, M.; Roman, V.M.; Perez, P. Do R&D activities matter for productivity? A regional spatial approach assessing the role of human and social capital. *Econ. Model.* **2017**, *60*, 448–461.
9. Sun, X.H.; Wang, Y.; Li, M.S. The influences of different R&D types on productivity growth in OECD countries. *Technol. Anal. Strateg. Manag.* **2016**, *28*, 651–663.
10. Hu, A.G.Z.; Jdfferson, G.H.; Qian, J. R&D and Technology Transfer: Firm-level Evidence from Chinese Industry. *Rev. Econ. Stat.* **2005**, *87*, 780–786.
11. Jefferson, G.H.; Bai, H.M.; Guan, X.J.; Yu, X.Y. R and D performance in Chinese Industry. *Econ. Innov. New Technol.* **2002**, *15*, 345–366. [CrossRef]
12. Corssman, G.; Helpman, E. *Innovation and Growth in the World Economy*; MIT Press: Gambridge, MA, USA, 1991.
13. Wu, Y.B. Indigenous R&D, Technology imports and productivity: Evidence from industries across regions of China. *Econ. Res.* **2008**, *8*, 51–64.
14. Sheng, J.C.; Zhang, S.; Li, Y. Heterogeneous governance capabilities, reference emission levels and emissions from deforestation and degradation: A signaling model approach. *Land Use Policy* **2017**, *64*, 124–132. [CrossRef]
15. Li, X.P. Own R&D, Technology purchased and productivity development. *J. Quant. Tech. Econ.* **2007**, *7*, 15–24.
16. Wan, L.L.; Zhu, Q. The effects of R&D input on industrial green total-factor productivity. *Econ. Dyn.* **2013**, *9*, 20–26.
17. Zhang, J.X.; Cai, N.; Mao, J.S.; Yang, C. Independent innovation, technology introduction and green growth of industry in China. *Stud. Sci. Sci.* **2015**, *33*, 185–194.
18. Chen, S.Y.; Goller, J. Green productivity growth in China's industrial economy. *Energy Econ.* **2014**, *44*, 89–98. [CrossRef]
19. Wang, Q.W.; Su, B.; Zhou, P.; Chiu, C.R. Measuring total-factor CO_2, emission performance and technology gaps using a non-radial directional distance function: A modified approach. *Energy Econ.* **2016**, *56*, 475–482. [CrossRef]
20. Yang, Y.; Cai, W.J.; Wang, C. Industrial CO_2 intensity, indigenous innovation and R&D spillovers in China's provinces. *Appl. Energy* **2014**, *131*, 117–127.
21. Han, X.F.; Hui, N.; Song, W.F. Can Informatization improve the technology innovation efficiency of Chinese industrial sectors. *China Ind. Econ.* **2014**, *12*, 70–82.
22. Färe, R.; Grosskop, S.; Pasurka, C.A., Jr. Environmental production functions and environmental directional distance functions. *Energy* **2007**, *32*, 1055–1066. [CrossRef]
23. Zhou, P.; Ang, B.W.; Wang, H. Energy and CO_2 emission performance in electricity generation: A non-radial directional distance function approach. *Eur. J. Oper. Res.* **2012**, *221*, 625–635. [CrossRef]
24. Zhang, N.; Choi, Y. Total-factor carbon emission performance of fossil fuel power plants in china: A metafrontier non-radial malmquist index analysis. *Energy Econ.* **2013**, *40*, 549–559. [CrossRef]
25. Oh, D.H. A metafrontier approach for measuring an environmentally sensitive productivity growth index. *Energy Econ.* **2010**, *32*, 146–157. [CrossRef]
26. Lanoie, P.; Laurent-Lucchetti, J.; Johnstone, N.; Ambec, S. Environmental policy, innovation and performance: New insights on the Porter Hypothesis. *J. Econ. Manag. Strategy* **2011**, *20*, 803–842. [CrossRef]
27. Wang, Y.; Shen, N. Environmental regulation and environmental productivity: The case of China. *Renew. Sustain. Energy Rev.* **2016**, *62*, 758–766. [CrossRef]
28. Lau, L.S.; Choong, C.K.; Eng, Y.K. Investigation of the environmental Kuznets curve for carbon emissions in Malaysia: Do foreign direct investment and trade matter? *Energy Policy* **2014**, *68*, 490–497. [CrossRef]
29. Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2007: The Fourth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2007.
30. Cheng, Z.H.; Li, L.S.; Liu, J. Industrial structure, technical progress and carbon intensity in China's provinces. *Renew. Sustain. Energy Rev.* **2018**, *81*, 2935–2946. [CrossRef]