sustainability

MDPI

Article

The Influence Mechanism of Bidirectional Foreign Direct Investment on Green Total Factor Productivity in China's Manufacturing Industry

Zongxian Feng [1], Huiting Hua [1] and Lingle Wang [2,*]

[1] School of Economics and Finance, Xi'an Jiaotong University, Xi'an 710049, China; zxfeng@mail.xjtu.edu.cn (Z.F.); sdw451821009@stu.xjtu.edu.cn (H.H.)
[2] School of Marxism, Xi'an Jiaotong University, Xi'an 710049, China
* Correspondence: 4122114010@stu.xjtu.edu.cn

Abstract: Recently, China has actively advocated green transformation in manufacturing. This paper applies the Malmquist–Luenberger (ML) index method to measure the green total factor productivity (GTFP) and its decomposition of 28 segments of China's manufacturing industry from 2004 to 2020; then, it empirically investigates their causal relationship and impact mechanism on bidirectional foreign direct investment (FDI). The results show that inward foreign direct investment (IFDI) and outward foreign direct investment (OFDI) significantly inhibit GTFP, whereas the interactive development level between the two (DFDI) significantly promotes GTFP during the sample period. After decomposing GTFP, it is found that IFDI or OFDI has a significant promotional effect on green technical change (GTC) but an inhibitory effect on green technical efficiency change (GEC), while DFDI has a promotional effect on GTC or GEC. Further research also finds that OFDI can effectively weaken the inhibitory effects in the long run; IFDI, OFDI, and DFDI have the same direction of impact on GTFP or GEC, only showing heterogeneity at the significant level, while their impact on GTC has uncertainty in different types of manufacturing industries. The more rational the manufacturing industry structure, the more significant the promotional effect of IFDI, OFDI, and DFDI on GTFP.

Keywords: inward foreign direct investment (IFDI); outward foreign direct investment (OFDI); green total factor productivity (GTFP); Malmquist–Luenberger (ML) index

check for updates

Citation: Feng, Z.; Hua, H.; Wang, L. The Influence Mechanism of Bidirectional Foreign Direct Investment on Green Total Factor Productivity in China's Manufacturing Industry. *Sustainability* **2024**, *16*, 6386. https://doi.org/10.3390/su16156386

Academic Editor: Mirco Peron

Received: 31 May 2024
Revised: 14 July 2024
Accepted: 23 July 2024
Published: 25 July 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

As China's "bringing in" and "going out" foreign opening policies steadily advance, the manufacturing sector has gradually transitioned from "unidirectional investment attraction" to "bidirectional investment attraction", meaning that both inward foreign direct investment (IFDI) and outward foreign direct investment (OFDI) in the manufacturing sector have shown significant growth. In 2022, the manufacturing sector's IFDI surged to CNY 323.7 billion, marking a 46.1% increase from the previous year, while its non-financial OFDI reached USD 21.6 billion, up by 17.4% (Statistical Bulletin of the People's Republic of China on National Economic and Social Development 2022—National Bureau of Statistics (NBS) (www.stats.gov.cn/sj/tjgb/ndtjgb/ (accessed on 30 May 2024))). The data show that the flow of bidirectional foreign direct investment (bidirectional FDI) in China's manufacturing sector has illustrated a homogeneous growth trend from 2004 to 2021 (Figure 1). However, the IFDI of the manufacturing industry has a "pollution haven" effect on the environment [1,2] in China. Meanwhile, Fu et al. [3] calculated the energy consumption of 28 sub-sectors in China's manufacturing industry, finding that it increased from 600 million tons of standard coal in 2000 to nearly 2 billion tons of standard coal in 2017, a 2.30-fold increase over 18 years, with carbon dioxide emissions increasing by 2.36-fold in the same period. The "Proposals of the Central Committee of the Communist Party of China on Formulating the Fourteenth Five-Year Plan for National

Economic and Social Development and the Long-Range Objectives Through the Year 2035", which was passed in October 2020, proposed to "maintain a basic stability in the share of manufacturing in the national economy" while emphasizing "accelerating the promotion of green and low-carbon development" in the manufacturing sector (Proposals of the Central Committee of the Communist Party of China on Formulating the Fourteenth Five-Year Plan for National Economic and Social Development and the Long-Range Objectives Through the Year 2035—Central Government Documents (www.gov.cn (accessed on 30 May 2024))). Energy conservation and environmental protection are closely related to the improvement of manufacturing productivity. Therefore, if China wants to realize a win–win situation between high-quality development of the manufacturing industry and environmental performance, improving green total factor productivity (GTFP) is undoubtedly a key part. If the impact of IFDI or OFDI on GTFP is studied in isolation, without considering the role of their interactive development (DFDI refers to the coordinated development effect of IFDI's technology spillover effect and OFDI's reverse technology spillover effect), the real impact of both on GTFP will be overlooked. In that case, is there some sense of logical connection between bidirectional FDI and GTFP in China's manufacturing industry? And through which channels do they affect GTFP? The answers to these questions are conducive to China's formulation of more effective international investment policies and have great theoretical and practical significance in promoting the green transformation of the manufacturing industry.

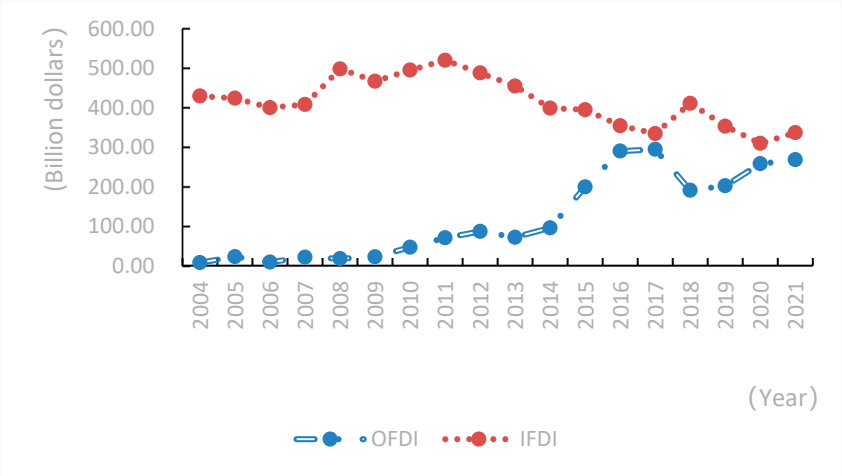


Figure 1. Flow rate of bidirectional FDI in China's manufacturing industry.

Scholars have discussed this research topic from different perspectives and reached various findings. Bidirectional FDI plays an important role in the impact on GTFP. Existing studies have shown that bidirectional FDI has a significant promotional effect on GTFP and is heterogeneous [4]. However, Ren and Zuo [5] found that bidirectional FDI significantly inhibited the growth of China's GTFP during the sample period, and the "pollution haven hypothesis" exists in our country. At the same time, Han et al. [6] found that in the short term, the comprehensive environmental effect of bidirectional FDI is positive, but in the long term, the comprehensive environmental effect of bidirectional FDI is negative.

Bidirectional FDI has an impact on GTFP through green technical change (GTC) and green technical efficiency change (GEC). GTFP can comprehensively reflect the productivity level of an industry because the decomposition of the growth rate of GTFP can effectively measure GTC and GEC. Therefore, we analyze the impact mechanism of bidirectional FDI on GTFP from the two paths of GTC and GEC.

Bidirectional FDI can impact GTFP through the pathway of GTC. The introduction of FDI in host countries generates technology spillovers for technological progress [7]. For example, the growth of environmental total factor productivity (ETFP) in China's high-energy-consuming industries is mainly driven by technical change (TC), and the

introduction of foreign advanced technology and equipment through IFDI is conducive to leveraging the learning effect and realizing technology spillover, which will promote the growth of ETFP [8]. IFDI also exacerbates environmental pollution and does not support the "Pollution Paradise Hypothesis" [9]. IFDI plays an inhibitory role in GTC, which will significantly inhibit GTFP. OFDI has a close link with TC. The link between China's OFDI and reverse green technological progress is an inverted U-shaped curve [10]. OFDI reverse technology spillover has a significant effect on China's technological progress [11], and also has a close link with the total factor productivity (TFP), and plays a larger role in driving TC [12]. OFDI also has a significant role in promoting GTC. OFDI motivated by the acquisition of advanced technology from abroad brings about domestic technological progress and can significantly lead to advancement in the domestic TFP. China's OFDI has led to domestic technological progress, which can significantly boost the domestic TFP [13], thus promoting the increase in GTFP [14]. Reverse technology spillovers of China's OFDI in manufacturing are highly correlated with the average productivity of the industry and its decomposition index [15]. OFDI has a significant positive impact on technological progress, but the effect is somewhat weak, and it transfers the results obtained to our country through the reverse technology spillover effect and ultimately enhances the level of China's TFP with the help of technology dissemination and diffusion [16].

Bidirectional FDI can impact GTFP through the pathway of GEC. IFDI mainly promotes the improvement of TFP through the channel of technical efficiency change (EC). Continued inflows of IFDI have created new knowledge-based clusters and technology spillovers in the regional economy [17]. At this stage, international R&D transmitted by outward investment has no significant positive impact on domestic technological progress. The positive reverse spillover effect of technological efficiency, total factor productivity, and outward investment has not yet appeared [18]. IFDI technology spillovers contribute to TFP and technological progress, and OFDI reverse technology spillovers achieves the same for both, but they both have a negative impact on technical efficiency [19]. For example, in Jiangsu Province, the annual average growth of the manufacturing industry's TFP is 2%, of which about 60% is contributed by EC. The difference in EC among industries is relatively significant, with little variation in TC [20]. External non-financial assistance seems to play an important role for the implementation of eco-efficiency actions at the firm level [21]. Manufacturing enterprises accelerate investment in more advanced and environmentally friendly production equipment to replace traditional backward production equipment and improve energy utilization efficiency through capital renewal while optimizing energy use structure, thereby achieving the green transformation. This has important policy implications for promoting the high-quality development of China's manufacturing industry [22].

The above literature, more or less, has indicated the important role that bidirectional FDI plays in the impact on GTFP. However, the existing research is still controversial over whether the impact of bidirectional FDI on GTFP is positive or negative, and scarcely researches the intrinsic driving forces behind the impact of bidirectional FDI on GTFP from the perspective of industry. Considering the aforementioned research results, we believe that existing studies have at least the following two areas for improvement: Firstly, the literature on the impact of bidirectional FDI on the industry-level GTFP of the manufacturing sector is still scarce, and it mostly explains the impact of bidirectional FDI on the GTFP of a certain region. Secondly, although there are considerable discussions on the contributions of TC and EC to TFP, the research results have a lot of limitations. These studies lack a comprehensive analysis of the impact of bidirectional FDI on the GTFP of the manufacturing industry, and even when they apply empirical methods to determine the impact of bidirectional FDI on TFP, most of them are grounded in IFDI and have opposite conclusions. Based on the current research as described above, this paper, on the one hand, applies the directional distance function and then combines the Malmquist–Luenberger (ML) index to scientifically measure the GTFP of 28 industries in China's manufacturing industry and its decomposition; on the other hand, by using a static panel model, this research empirically explores the mechanisms of the impact of IFDI, OFDI, and DFDI on

China's manufacturing industry's GTFP and its decomposition, aiming to provide empirical evidence for the manufacturing industry's further opening up and green transformation.

2. Theoretical Analysis

2.1. The Mechanism of IFDI's Impact on the Manufacturing Industry's GTFP

This paper decomposes the pollution effect of IFDI on the environment into scale effects, structure effects, and technology effects [23]. IFDI impacts the host country's environment through these three effects, thereby affecting GTFP [24].

2.1.1. Scale Effect Mechanism

The scale effect means that IFDI will lead to an increase in the capital stock of the host country. This increase in capital stock leads to an expansion of the economic scale, which will aggrandize pollutant emissions. The industries transferred from developed countries to China are not only pollution-intensive but also include "clean" industries [25]. Therefore, the scale effect of IFDI on GTFP manifests in two aspects: one is the positive impact. After the investment in Lafarge and the recovery of the first and second production lines, production significantly increased and the costs significantly reduced. KCMC benefited from economies of scale [26]. IFDI has a weaker promotional effect on TFP improvement in industries but a higher promotional effect on ETFP and environmental technical efficiency change. However, its positive impact on environmental technical change is not significant. The increase in the proportion of IFDI leads to industry environmental technology closer to the frontier, resulting in a "pollution halo" effect [27]. Consequently, IFDI indirectly fosters GTFP enhancement [28]. The second is the negative impact. Resource-seeking IFDI has promoted the expansion of resource-intensive manufacturing, forming a scale effect, which to some extent has aggravated environmental pollution [29], easily leading to ecological crises or a "resource curse" [30]. General research believes that the rapid development of IFDI expands the scale of domestic production activities, especially leading to the scale expansion of polluting industries, causing excessive consumption of natural resources and an increase in total pollution emissions, thereby resulting in lower GTFP [31]. The increased cost of pollution control invested by enterprises to some extent squeezes out the enterprises' R&D investment, thereby hindering TC. With lax industry government regulation and less resistance to foreign capital entry, IFDI in China's manufacturing industry exhibits a "pollution haven" effect [2]. IFDI has a significant inhibitory effect on China's GTFP, verifying the "pollution haven" hypothesis [32].

2.1.2. Structure Effect Mechanism

The structure effect denotes the impact of IFDI inflow on the host country's industrial structure and consequently on the environment, further affecting GTFP. Market-seeking IFDI entering the manufacturing industry will produce a competitive effect, forcing domestic manufacturing enterprises to improve technology, eliminate a large number of backward capacities, and optimize the industrial structure [33]. For developing countries, due to low development levels and industrial structures in the process of industrialization, most IFDI enters pollution-intensive industries, so the industry structure effect is negative [24]. Resource-seeking and efficiency-seeking IFDI invested in China targets China's resource-intensive and cheap labor factors and mostly flows to low-value-added labor-intensive processing and manufacturing industries, further reflecting the transfer of pollution industries from developed countries, with a limited effect on China's industrial structure and technological upgrading [34], to some extent leading to the current slow adjustment speed of China's manufacturing industry structure, high energy consumption, and large amount of pollution emissions [35].

2.1.3. Technology Effect Mechanism

The technology effect means that local firms in the host country reduce the pollutant emissions of the firm or the industry by imitating and learning advanced clean technologies.

The direction of the technological effect depends on the technology spillover effect of IFDI [36], and the strength of technology spillover from IFDI depends to a large extent on the host country's domestic enterprises' technology absorption capacity [37].

Correspondingly, the impact of IFDI on GTFP also shows significant industry heterogeneity. Compared to lightly polluting capital-intensive industries, the "pollution haven" effect of IFDI is more pronounced in labor-intensive and highly polluting capital-intensive industries [2]. IFDI inflows increase undesired output in labor-intensive and highly polluting capital-intensive industries, thus discouraging GTFP in manufacturing. Based on this, the theoretical transmission mechanism of IFDI's impact on GTFP in this paper is shown in Figure 2.

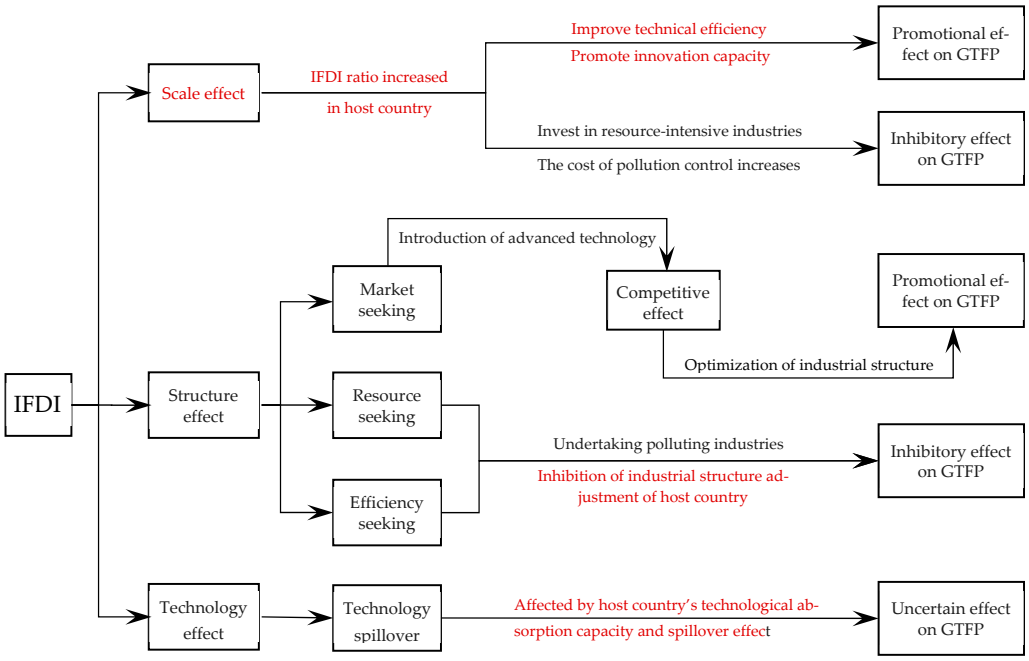


Figure 2. Theoretical transmission mechanism of IFDI's impact on GTFP.

2.2. The Mechanism of OFDI's Impact on the Manufacturing Industry's GTFP

OFDI mainly affects the transformation and upgrading of the home country's industries through pathways such as industrial structure optimization and reverse technology spillover, and the home country's industrial upgrading, in turn, impacts GTFP through technological and structural effects. Meanwhile, OFDI is divided into "path-wise FDI" and "inverse FDI" directions [38].

One aspect involves the technology effect mechanism. In its initial stage, OFDI primarily targets developing countries, manifesting a significant motive for technology export. Meanwhile, market-seeking and resource-seeking OFDI leverage technological comparative advantages to drive the export of traditional manufacturing technology equipment from the home country. In addition, the lower level of absorptive capacity of manufacturing firms also prevents OFDI reverse technology spillover from significantly enhancing TC in the home country. Hence, the promotion of TC by OFDI is not evident, and its technological impact is limited [38]. Whether OFDI's reverse green technology spillover significantly affects the GTFP of the home country may depend on the absorptive capacity of the home country [39]. By acquiring Corus, India's Tata-Corus steel company could link their labor-intensive production with the production of raw materials, while at the same time obtaining access to the highly profitable markets of the developed Western countries through Corus' high technology, gaining management experience and skills [26]. OFDI's reverse technology spillover does not significantly promote the growth of GTFP in the manufacturing industry during the sample period [40]. "Inverse" OFDI is more targeted at acquiring advanced production technologies from developed countries, enhancing the

production efficiency of home country companies, and improving resource utilization efficiency through reverse technology spillover [41], thus exerting a technology effect. For example, through mergers and acquisitions, China's Wanxiang Group not only owns a large number of product patents and advanced testing technology centers but also has an excellent R&D team to realize the technological upgrading of its domestic parent company [42]. Huawei's OFDI has a clear market orientation. From 1999 to 2012, Huawei set up research institutes in India, Sweden, the United States, Germany, the United Kingdom, France, and Finland, and cooperated with Siemens and Symantec to establish joint ventures. Huawei's technology-acquiring OFDI has enhanced Huawei's technological strength and the quality of its products and services. A series of initiatives and active participation in international competition have gradually allowed Huawei to improve its own technological level, introduce the technology of international companies, and then digest and absorb the technology and further make some improvements in functions, characteristics, and integration capabilities [43]. The reverse green technology spillover effect of OFDI, which exists in China, significantly promotes GTFP growth and becomes a new driver for enhancing China's GTFP in the new era [44], and exhibits a nonlinear law of positive marginal efficiency increase [45]. Technology-seeking OFDI contributes more to GTFP than resource-seeking OFDI and market-seeking OFDI [46].

Another aspect is the mechanism of structure effects. "Path-wise" OFDI more often relocates domestic low-end, high-energy-consuming manufacturing enterprises to host countries with cheaper production factors, providing space for domestic industrial structure upgrading [47], thus exerting a structure effect, promoting clean production, reducing pollutant emissions, and improving environmental quality. For example, resource-seeking and efficiency-oriented "path-wise" OFDI relocates domestic low-end, high-energy-consuming enterprises to host countries with cheaper production factors, providing space for domestic industrial structure optimization [48]. Additionally, due to the lagging nature of the reverse technology spillover of "inverse" OFDI in improving industrial technology levels [49], and given the relatively slow speed of China's industrial structure adjustment, the structure effect also has a limited impact in the short term. Only under certain conditions does OFDI show a significant positive effect on the rationalization of industrial structure [50]. Only the coordinated development of OFDI and industrial structure upgrading will significantly promote the improvement of GTFP in China [51]. Market-seeking OFDI drives the export of traditional manufacturing technology equipment from the home country by using technological comparative advantages. However, the large-scale OFDI growth realized by the home country in the short term will, to a large extent, give rise to the emergence of low-value-added, high-energy-consuming, and high-polluting industries, which will have a negative impact on the ecological environment and hinder GTFP improvement [48]. Based on this, the theoretical transmission mechanism of OFDI's impact on GTFP in this paper is shown in Figure 3.

2.3. The Mechanism of DFDI Impact on the Manufacturing Industry's GTFP

In the 1980s, Dunning's stages of development theory of FDI pointed out that with the improvement of economic development level, the interactive effect between IFDI and OFDI would significantly strengthen, asserting that IFDI would be the basis of OFDI, and OFDI strongly would support the higher development of IFDI [52]. Huang et al. [53], using the panel vector autoregression model, also found that DFDI can promote the improvement of economic growth quality [7]. The increase in DFDI will significantly curb environmental pollution, and enhancing DFDI in the future is one of the important ways to reduce emissions [54], and DFDI can improve the increase in GTFP [55,56]. However, Zhang et al. [57] found that the impact of bidirectional FDI on GTFP presents an "inverted U"-shaped relationship. Only when the commodity market segmentation index and factor market segmentation index exceed a certain threshold will the bidirectional FDI have an obvious inhibitory impact on GTFP. Thus, it can be concluded that the comprehensive impact direction of DFDI on GTFP is uncertain.

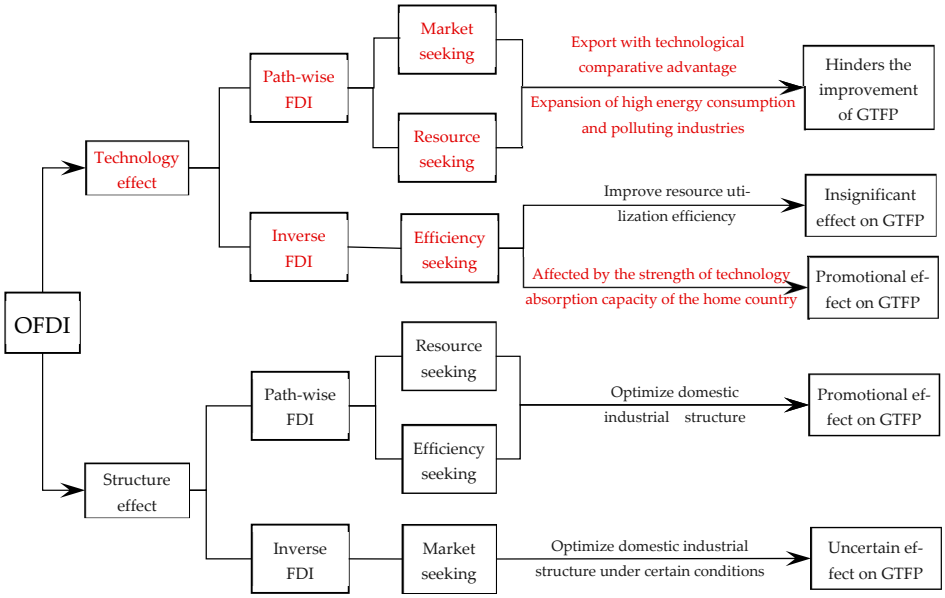


Figure 3. Theoretical transmission mechanism of OFDI's impact on GTFP.

3. Research Design

3.1. Research Scheme

Many previous studies on this topic have laid the foundation for this paper, whose methods, variables, data, and conclusions are shown in Appendix A. However, as mentioned in the introduction, although the existing literature has studied relevant issues from multiple perspectives, there are still some research gaps that can be supplemented. Based on the above theoretical analysis, this study is based on China's dual identity on the international capital stage as both an investor and host country, combining Dunning's three major foreign investment motive theories of efficiency seeking, resource seeking, and market seeking [58], and rooted in the theoretical transmission mechanism of China's bidirectional FDI through affecting GTC and GEC, and then the GTFP of China's manufacturing. The mechanism of the bidirectional FDI's impact on GTFP is notably complex. Can bidirectional FDI effectively promote the GTFP growth of the manufacturing industry? Addressing this question requires further examination. Given the sparse academic discourse on this subject, this paper explores the comprehensive impact mechanisms of bidirectional FDI on the manufacturing sector's GTFP. Based on these, the complete mechanism function and empirical tests taken in this paper to verify the following four hypotheses are shown in Figure 4.

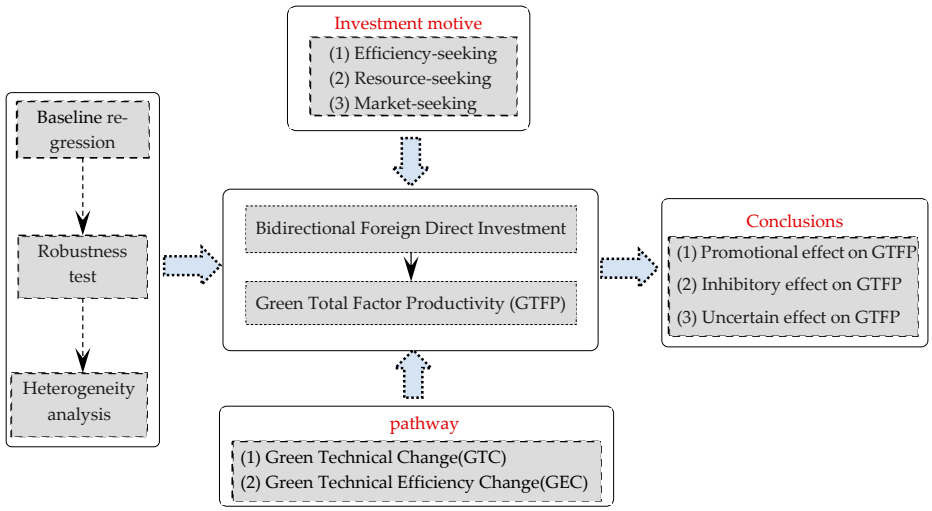


Figure 4. Diagram of the mechanism function and empirical tests.

Hypothesis 1. *The impact of IFDI on manufacturing GTFP is uncertain.*

Hypothesis 2. *The influence of IFDI on the GTFP of different manufacturing industries exhibits heterogeneity.*

Hypothesis 3. *Controlling for other factors, the impact of OFDI on the manufacturing industry's GTFP is uncertain.*

Hypothesis 4. *DFDI influences the manufacturing industry's GTFP, and the direction and mechanism of the effect are yet to be tested.*

3.2. Econometric Model Setting

To examine the effect of bidirectional FDI on the GTFP across 28 industries within China's manufacturing sector, this study employs traditional econometric methodologies, assuming that the production of each industry in China's manufacturing sector conforms to the Cobb–Douglas production function. Drawing on the practice of Cui and Lin [59] in transforming the types of production factor inputs in the production function, and Solow's [60] idea of representing TFP as the residual of the output economic growth rate after deducting the contributions of labor and capital, the production function utilized herein is delineated as follows:

$$Y_{it} = A_{it}(M_{it}^{\gamma})L_{it}^{\alpha}K_{it}^{\beta} \tag{1}$$

In this formula, Y_{it}, $A_{it}(\cdot)$, M_{it}, L_{it}, and K_{it} are, respectively, the total output, GTFP function accounting for energy consumption and undesirable outputs, intermediate inputs other than capital and labor, labor, and capital of industry i in period t; γ, α and, β are, respectively, the output elasticity of intermediate input, the output elasticity of labor, and the output elasticity of capital. Referring to the practice of Hulten et al. (2006) [61], it is assumed that $A_{it}(\cdot)$ satisfies Hicks neutrality, and its components are multivariate combinations; then,

$$M_{it}^{\gamma} = FDI_{it}^{\gamma_j} X_{it}^{\gamma_n} A_{it}(M_{it}^{\gamma}) = A_{i0} FDI_{it}^{\gamma_j} X_{it}^{\gamma_n} \tag{2}$$

Here, A_{i0} represents the initial productivity level. Depending on the value taken for j, FDI_{it} represents, respectively,$IFDI_{it}$, $OFDI_{it}$, and $DFDI_{it}$ of industry i in period t; X indicates other factors affecting GTFP, that is, the control variables of this paper: $j = 1, 2, 3$; $n = 1, 2, 3, 4, 5, 6$. Substituting Equation (2) into Equation (1) yields

$$Y_{it} = A_{i0} FDI_{it}^{\gamma_j} X_{it}^{\gamma_n} L_{it}^{\alpha} K_{it}^{\beta} \tag{3}$$

Based on the definition of GTFP, dividing both sides of Equation (3) by $L_{it}^{\alpha}K_{it}^{\beta}$ yields

$$GTFP_{it} = A_{i0} FDI_{it}^{\gamma_j} X_{it}^{\gamma_n} \tag{4}$$

After taking the logarithm of Equation (4), we obtain the econometric model for the relationship between bidirectional FDI and GTFP as Equation (5):

$$\ln GTFP_{it} = \ln A_{i0} + \sum_{j=1}^{3} \gamma_j \ln FDI_{it} + \sum_{n=1}^{5} \gamma_n \ln X_{it} \tag{5}$$

In this paper, we assume that output-oriented CRS returns to scale remain unchanged [62] and refer to Wang [9] to further decompose the GTFP into the product of GTC and GEC. Therefore, after taking the logarithm, GTFP equals the sum of GTC and GEC. The calculated GTC and GEC of each industry in China's manufacturing sector are used to replace the GTFP in Equation (5), respectively, as follows:

$$\ln GTC_{it} = \ln A_{i0} + \sum_{j=1}^{3} \gamma_j \ln FDI_{it} + \sum_{n=1}^{5} \gamma_n \ln X_{it} \quad (6)$$

$$\ln GEC_{it} = \ln A_{i0} + \sum_{j=1}^{3} \gamma_j \ln FDI_{it} + \sum_{n=1}^{5} \gamma_n \ln X_{it} \quad (7)$$

By applying Equations (6) and (7), we can discern whether the effect of bidirectional FDI affecting GTFP in manufacturing originates from GTC or GEC.

3.3. Data Source and Preprocessing

Considering the availability of data and the consistency of statistical caliber, this paper considers more sub-sectors of China's manufacturing industry as soon as possible for the accuracy and robustness of the results. Without compromising empirical testing, the sample selected for this paper consists of panel data from China's 28 manufacturing sub-industries for the years 2004–2020. During this period, the "National Economic Industry Classification" national standard underwent revisions in the versions of GB/T 4754-2002, GB/T 4754-2011, and GB/T 4754-2017 [63]. This study adheres to the manufacturing industry classification at the two-digit level as per the 2011 version (the National Bureau of Statistics implemented the 2002 standard of industrial classification of the National Economy from 2003 to 2011, and the 2011 standard of industrial classification has been implemented since 2012. The 2002 standard has little difference from the 2011 standard, which can be merged. However, the industry classification standard implemented before 2003 is very different from the 2002 standard and 2011 standard, and the combined data are not reliable). Following the industry consolidation principles used by Chen [64], industries such as the "Waste Resource and Scrap Material Recycling and Processing Industry", the "Metal Products, Machinery and Equipment Repair Industry", and "Other Manufacturing" were excluded. The "Rubber Products Industry" and "Plastic Products Industry" before 2011 were merged into the "Rubber and Plastic Products Industry"; the "Transportation Equipment Manufacturing Industry" was divided into the "Automobile Manufacturing Industry" and "Railway, Shipbuilding, Aerospace, and Other Transportation Equipment Manufacturing Industry"; "Arts and Crafts Manufacturing" was divested from "Arts and Crafts and Other Manufacturing" and merged with "Arts, Educational and Sporting Goods Manufacturing" to form a new "Cultural, Educational and Sporting Goods Manufacturing"; "Cultural and office machinery manufacturing" in "Instrumentation and Cultural and Office Machinery Manufacturing" is transferred to the old "General Equipment Manufacturing" to form the new "General Equipment Manufacturing" and "Instrumentation Manufacturing". Finally, this resulted in 28 sub-industries under the manufacturing category, as shown in Table 1.

Table 1. China's 28 manufacturing sub-industries.

Industry Code	Industry Name	Industry Code	Industry Name
C13	Food Processing from Agricultural Products	C27	Pharmaceutical Manufacturing
C14	Food Manufacturing	C28	Chemical Fiber Manufacturing
C15	Wine, Beverage, and Refined Tea Manufacturing	C29	Rubber and Plastic Product Industry
C16	Tobacco Products	C30	Non-Metallic Mineral Products Industry
C17	Textile Industry	C31	Ferrous Metal Smelting and Rolling Processing Industry
C18	Textile Clothing and Apparel Industry	C32	Non-Ferrous Metal Smelting and Rolling Processing Industry
C19	Leather, Fur, Feathers and their products and Footwear Industry	C33	Metal Product Industry
C20	Wood Processing and Products of Wood, Bamboo, Rattan, Palm, and Straw	C34	General Equipment Manufacturing Industry

Table 1. *Cont.*

Industry Code	Industry Name	Industry Code	Industry Name
C21	Furniture Manufacturing	C35	Special Equipment Manufacturing Industry
C22	Paper making and Paper Products	C36	Automobile Manufacturing
C23	Printing and Reproduction of Recorded Media	C37	Railway, Shipbuilding, Aerospace, and Other Transportation Equipment Manufacturing Industry
C24	Manufacturing of Articles for Culture, Education, and Sports	C38	Electrical Machinery and Equipment Manufacturing
C25	Petroleum, Coal, and other Fuel Processing Industry	C39	Computer, Communication, and Other Electronic Equipment Manufacturing
C26	Chemical Raw Materials and Chemical Product Manufacturing	C40	Instrument and Meter Manufacturing Industry

All data were sourced from the "China Statistical Yearbook", "China Industrial Statistics Yearbook", "China Science and Technology Statistics Yearbook", "China Energy Statistics Yearbook", "China Environmental Statistics Yearbook", and "China Economic Census Yearbook".

3.4. Variable Measurements

3.4.1. Dependent Variables

The dependent variables are, respectively, GTFP, GTC, or GEC of the manufacturing industry. The traditional method for measuring TFP is the Solow residual method. In reality, it is difficult to meet the premise assumption of 100% technical efficiency in terms of the productivity change of economic decision-making units [65], and at the same time, the data envelopment analysis (DEA) method based on the output perspective not only does not need to set up a specific production function, but also has the advantage of measuring multiple inputs and multiple outputs [66]. So, in this paper, each segment of the selected 28 manufacturing industries is regarded as a decision unit, and the MaxDEA 12.1 software is used to measure the GTFP of the manufacturing industry based on the ML index method. The Malmquist index was developed by Swedish economist and statistician Malmquist [67] in 1953 to analyze the changes in productivity over time. Färe et al. [68] developed the Malmquist productivity index used to examine TFP. Chung et al. [69] applied the direction of distance function including bad output to the Malmquist model and referred to any Malmquist index derived from a Malmquist model that includes bad output as the ML index. When measuring the ML index, we refer to the approach of Gu and Zhao [70], which considers both "good output" and "bad output". The "good output" is expressed by the total industrial output of each sub-sector of the manufacturing industry. Given the changes in the statistical indicators of industrial enterprises above designated size in manufacturing industries after 2012, the total output value of industrial enterprises above designated size in manufacturing industries for 2004–2011, the main business income for 2012–2017, and the business income for 2018–2020 are used to characterize the total output in the study period. To eliminate the influence of price factors on the changes in total output, we used the ex-factory prices of industrial producers in the sub-industries to deflate the value of the total output of the industry, which was finally converted to the value calculated at constant 2003 prices. The "bad output" is very complex and difficult to portray comprehensively and accurately. Based on the importance of the impact of pollution and the completeness of the data resources, the emissions of wastewater, exhaust gas, and solid waste from industrial enterprises above designated size in manufacturing industries were chosen as the "bad output". In terms of inputs, in addition to labor inputs and capital inputs, energy inputs are also considered. Capital inputs are expressed in terms of capital stock, which is calculated using the perpetual inventory method with the following formula:

$$K_{it} = I_{it} + (1 - \delta_{it})K_{it-1} \quad (8)$$

where K_{it} and K_{it-1}, respectively, represent the capital stock of industry i in periods t and $t-1$; I_{it} indicates additional capital investment in industry i in period t; and δ_{it} is the depreciation rate of capital in industry i in period t.

In actual calculations, following Chen's [64] approach, the capital depreciation rate (δ_{it}) is derived through the following process: Step 1 is to calculate the cumulative depreciation in period t which equals the original value of fixed assets in period t minus the net value of fixed assets in period t. Step 2 is to calculate the depreciation of the current year in period t which equals accumulated depreciation in period t minus accumulated depreciation in period $t-1$. Step 3 is to calculate the capital depreciation rate in period t which equals the current year's depreciation in period t divided by the original value of fixed assets in period $t-1$. The year-end net fixed assets of each manufacturing industry segment in 2003 were used as the base year capital stock, and the new capital investment in that year was expressed by using the current year's investment in manufacturing fixed assets which equals the current year's original value of fixed assets minus the previous year's original value of fixed assets. Current-year fixed asset investment in manufacturing is obtained by deflating the fixed asset investment price index by using 2003 as the base period. Labor input is expressed by the annual average number of employees in each sub-sector of the manufacturing industry.

Energy input is expressed as the total annual consumption of standard coal in each segment of the manufacturing industry. Additionally, the ML index method calculates the index as the ratio of the current year to the previous year, that is, the change rate relative to the previous year. Therefore, drawing on the approach of Cheng and Lu [71], this paper sets the base period of 2004 as 1, and further calculates the comparable GTFP of the manufacturing industry using the ML index, and then decomposes the index into GTC and GEC. GTC measures changes in the ratio of maximum possible output on different frontiers, reflecting changes in productivity due to pure technical changes, while GEC measures changes in the ratio of actual output to maximum possible output, reflecting changes in efficiency assuming constant skill level.

3.4.2. Explanatory Variables

The main explanatory variables are IFDI, OFDI, and DFDI. Given that the "China Statistical Yearbook" only provides annual OFDI and IFDI data for the manufacturing industry, it lacks annual OFDI and IFDI data for manufacturing sub-industries. Because of the industry heterogeneity in manufacturing bidirectional FDI and significant differences between different sub-industries [57], this paper adopts the methods of Zhao and He [72] to estimate OFDI and IFDI in manufacturing segments through Equations (9) and (10):

$$IFDI_{it} = \frac{w_{it}}{w_t} \times IFDI_t \tag{9}$$

$$OFDI_{it} = \frac{c_{it}}{c_t} \times OFDI_t \tag{10}$$

Here, $IFDI_{it}$ indicates FDI in manufacturing sub-sectors by sub-industry i in period t, and $IFDI_t$ indicates the total FDI by the manufacturing sector in period t; $OFDI_{it}$ indicates OFDI in manufacturing sub-sector by sub-industry i in period t, and $OFDI_t$ indicates the total OFDI by the manufacturing sector in period t. Additionally, referencing the UNCTAD database, it is found that the actual amounts used of FDI by industry published by the National Bureau of Statistics of China are flow data. Therefore, $IFDI_t$ and $OFDI_t$ utilize the flow data of bidirectional FDI for the manufacturing industry from 2004 to 2020. w_{it} indicates the foreign capital in the manufacturing sector of sub-industry i in period t, and w_t indicates the total foreign capital in the manufacturing sector in period t; c_{it} indicates the export delivery value in the manufacturing sector of sub-industry i in period t, and c_t indicates the total export delivery value of the manufacturing sector in period t. The annual foreign capital and export delivery value of the manufacturing sector are obtained by deduction. That is, the annual foreign capitalization and export delivery value of the

manufacturing industry are subtracted from the annual foreign capitalization and export delivery value of the industry above the designated size by the foreign capitalization and export delivery value of the mining industry, as well as the foreign capitalization and export delivery value of the electricity, heat, gas, and water production and supply industry.

Considering the DFDI, drawing on the research results by Liu et al. [73] and Huang et al. [53], the formula for measuring DFDI in China's manufacturing industry segments is $DFDI_{it} = \{IFDI_{it} \times OFDI_{it}/[(IFDI_{it} + OFDI_{it})/2]\}^{1/2}$. Meanwhile, $Dfdi_{it}$ is used to indicate DFDI in the manufacturing sector of sub-industry i in period t.

3.4.3. Control Variables

The rationalization of industrial structure refers to the aggregation quality between industries, reflecting both the coordination level among industries and the degree of effective resource utilization. In essence, it measures the coupling degree of input structure and output structure. The assessment of industrial structure rationalization primarily focuses on resource allocation theory, emphasizing the distribution, coordination, and efficiency of factor resources among industries. This paper, drawing on previous studies by domestic and international scholars, selects the degree of deviation from the industrial structure (Tsge) and the optimized degree of deviation from the industrial structure (Tsgx) [74] to measure the rationalization of industrial structure. Tsge and Tsgx are calculated as shown below.

$$Tsge_{it} = \sum_{i=1}^{n} \left| \frac{Y_{it}/L_{it}}{Y_t/L_t} - 1 \right| = \sum_{i=1}^{n} \left| \frac{Y_{it}/Y_t}{L_{it}/L_t} - 1 \right| \quad (11)$$

$$Tsgx_{it} = \sum_{i=1}^{n} \left(\frac{Y_{it}}{Y_t} \right) \left| \frac{Y_{it}/L_{it}}{Y_t/L_t} - 1 \right| \quad (12)$$

In Equations (11) and (12), $Tsge_{it}$ represents the structural deviation degree of the manufacturing sub-industry i in period t, $Tsgx_{it}$ represents the optimized structural deviation degree of the manufacturing sub-industry i in period t, Y_{it} denotes the total output value of the manufacturing sub-industry i in period t, Y_t represents the total output value of the selected 28 manufacturing sub-industries' industrial enterprises above designated size in manufacturing industries, L_{it} denotes the average number of all employees of industrial enterprises above designated size in manufacturing industry segment i in period t, and L_t indicates the average number of all employees of industrial enterprises above designated size in the 28 manufacturing sub-sectors selected in this paper in period t; n denotes the number of the selected 28 manufacturing sub-industries. A higher Tsge value indicates a more irrational structure of the manufacturing sub-industry. Tsgx not only retains the advantages of the degree of deviation from the industrial structure but also uses the weighted output value of manufacturing sub-industries, reflecting the significance of each manufacturing sub-industry. A smaller Tsgx value suggests a more irrational structure of the manufacturing sub-industry.

Referring to the research results by Xu et al. [75], the proportion of government funds in the source of the scientific research funding of industrial enterprises above the designated size in manufacturing industries is used to measure the government input funds (Gov), which indicates the degree of government support for the segmented industries; referring to the research results by Huang et al. [53], institutional quality (d1) is measured by the proportion of foreign capital to the industry's actual capital, ownership structure (d2) is measured by the proportion of state capital to actual capital, and material capital per labor (d3) is measured by the ratio of the average balance of net fixed assets to the number of employees at the end of the year. Due to the availability of data and with reference to the 2013 Economic Census Yearbook, this paper characterizes material capital per labor in terms of the ratio of the total number of fixed assets of industrial enterprises above the designated size in manufacturing industries to the number of employees at the end of the year.

4. Estimation Results and Description

We used stata17.0 to obtain descriptive statistics for each variable (see Table 2). According to the statistical results, among the capital flow of bidirectional FDI in the manufacturing industry from 2004 to 2020, the annual average value of IFDI was the largest, accounting for about 77.27% of bidirectional FDI capital flow, and OFDI only accounted for 22.73% of bidirectional FDI capital flow. From the standard deviation and the comparison between the maximum value and the minimum value, it can also be found that there is a large gap in the value of IFDI, OFDI, and DFDI between different manufacturing segments, showing significant industrial differences. The average value of the segments' GTFP is relatively close to the average value of GTC, but there exists a certain gap with the average value of GEC, which to some extent also shows that the GTFP of China's manufacturing industry is mainly improved through GTC. The statistics of variance, maximum, and minimum value of the manufacturing industry segments also show that there is a large gap in GTFP, GTC, and GEC.

Table 2. Statistical characteristics of variables.

Variable	Observed Value	Cross-Section Number	Mean	Standard Deviation	Median	Min Value	Max Value
GTFP	476	28	1.4940	0.6317	1.3689	0.5397	7.0078
GTC	476	28	1.6511	0.7901	1.5374	0.4240	7.4546
GEC	476	28	1.0594	0.5870	0.9517	0.1174	3.6614
IFDI	476	28	14.5023	20.2864	8.0000	0.0004	121.5351
OFDI	476	28	4.2658	16.2316	0.9491	0.0040	171.1078
DFDI	476	28	1.6001	1.5003	1.2200	0.0291	10.9789
Tsge	476	28	0.5244	0.7028	0.3322	0.0004	5.2947
Tsgx	476	28	0.0179	0.0300	0.0068	0.0000	0.2211
Gov	476	28	3.3690	4.0646	2.3962	0.0836	27.9637
d1	476	28	0.1541	0.0901	0.1440	0.0000	0.4923
d2	476	28	0.1177	0.1258	0.0799	0.0016	0.8950
d3	476	28	22.6918	17.2606	18.4099	2.1705	89.8002

4.1. Estimation Results and Analysis of the Overall Manufacturing Industry

This study utilizes panel data from 28 manufacturing sub-industries for the years 2004–2020 to test Hypotheses 1, 2, 3, and 4. The estimation methods applicable to static short panels include Pooled OLS (POLS), fixed effects (FE), and random effects (RE). To select the most effective estimation method, F-tests and LM tests were conducted to examine the presence of individual effects. If individual effects did not exist, POLS would be applied. If individual effects were present, a Hausman test would be performed to decide between the FE and RE models.

To avoid pseudo-regression and to ensure the validity of the estimation results, a unit root test must be performed on all the variables in this paper before performing the regression analysis. Due to the LLC method applied only to long panels, this paper used the unit root test (HT test) which was proposed by Harris and Tzavalis and designed for panels where T is fixed and $n \to \infty$. The unit root test results indicate that all variables are significant at the 1% level, suggesting that the panel data are generally stationary.

Additionally, to test the issue of multicollinearity among IFDI, OFDI, and DFDI with GTFP, a multicollinearity test, where the Variance Inflation Factor (VIF) values of the variables were calculated, was performed using Stata. The results showed that the tolerance levels of all variables were not less than 0.1, and the highest VIF was 2.38, far below 10, which indicated no severe multicollinearity issues among the variables.

Regarding the estimation of panel models, the endogeneity of variables was also considered. IFDI, OFDI, and DFDI with GTFP may form a reciprocal causal relationship; i.e., IFDI, OFDI, and DFDI may affect GTFP, and GTFP may also affect IFDI, OFDI, and DFDI. If there are endogenous variables in the panel model, fixed-effects estimation results

may be biased. Therefore, before conducting regression estimation, we need to test whether the model used has an endogeneity problem. In this paper, the IV estimation of models (1), (4) and (6) uses the one-stage lagged variables of IFDI, OFDI, and DFDI as instrumental variables, and then employs the D-M test proposed by Davidson–MacKinnon (1993) to determine whether endogenous variables are present or not. The p-values of the D-M test for these three models were non-zero, accepting the null hypothesis that explanatory variables are uncorrelated with the contemporaneous error terms, indicating no significant endogeneity issues. The regression results of the sample are shown in Table 3.

Table 3. Estimation results of the overall manufacturing industry.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	FE	RE	RE	FE	RE	FE
	lnGTFP	lnGTC	lnGEC	lnGTFP	lnGTC	lnGEC
dlnIFDI	−0.077 **	0.013	−0.087 *	−0.096 ***	0.011	−0.135 ***
	(−2.52)	(0.39)	(−1.84)	(−3.51)	(0.30)	(−3.03)
dlnOFDI	−0.097 ***	0.034	−0.127 ***	−0.062 ***	0.049 **	−0.119 ***
	(−4.38)	(1.41)	(−3.72)	(−3.36)	(2.02)	(−3.98)
lnDFDI	0.359 ***	0.084 ***	0.233 ***	0.180 ***	0.046	0.169 **
	(13.81)	(3.07)	(6.12)	(4.48)	(1.04)	(2.58)
lnTsge				−0.823 ***	0.240 ***	−1.121 ***
				(−17.25)	(4.60)	(−14.45)
lnTsgx				0.786 ***	−0.182 ***	1.023 ***
				(16.93)	(−3.66)	(13.56)
lnGov				−0.053 ***	−0.059 **	−0.003
				(−2.80)	(−2.28)	(−0.09)
lnd1				0.143 ***	0.007	0.188 ***
				(4.80)	(0.20)	(3.87)
lnd2				−0.111 ***	0.070 **	−0.183 ***
				(−4.62)	(2.26)	(−4.67)
lnd3				0.249 ***	0.110 *	0.126
				(4.74)	(1.83)	(1.48)
Constant	0.294 ***	0.414 ***	−0.112	2.512 ***	−0.248	3.103 ***
	(22.40)	(6.54)	(−1.38)	(10.76)	(−0.92)	(8.18)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No	No
Mean VIF	1.02	1.02	1.02	2.83	2.83	2.83
F-value	66.61 ***			81.66 ***		41.41 ***
Wald value		12.67 ***	47.85 ***		72.96 ***	
*R*2	0.324			0.641		0.476
F-test	21.99 ***			43.23 ***		36.65 ***
LM Test		1074.91 ***	896.22 ***		916.37 ***	
Hausman Test	45.49 ***			140.16 ***		79.61 ***
D-M Test	0.330			0.019		0.111
N	448	448	448	448	448	448

Note: The numbers in brackets are the t statistics corresponding to the regression coefficient; ***, ** and * indicate that they have passed the significance test at the 1%, 5% and 10% confidence levels, respectively, with the same interpretations below.

The regression results for the sample indicate that models (1), (2), and (3) demonstrate that IFDI has a significant negative impact on GTFP, while the impact on GTC is not significant but positive, and the impact on GEC is more significantly negative and greater than the impact on GTC. The impact of OFDI on GTFP is significantly negative, while the impact on GTC is insignificant but positive, and the impact coefficient on GEC is also significantly negative and greater than the impact coefficient on GTC. DFDI, however, has a significantly positive impact on GTFP, which is greater than the impact on GTFP of IFDI and OFDI, and a significantly positive impact on GTC and GEC, and the impact on GEC is larger than the impact on GTC. The above shows that IFDI, OFDI, and DFDI mainly

affect GTFP through GEC, and DFDI is one of the important ways to improve GTFP in the future. After incorporating control variables, models (4), (5), and (6) maintain consistent relationships and significance levels between the manufacturing industry's IFDI, OFDI, and DFDI with GTFP, GTC, or GEC. This further indicates that the impacts of IFDI and OFDI on GTFP or GEC are negative and pass higher levels of significance testing, while their impact on GTC is positive but not significant. Therefore, Hypotheses 1 and 3 are substantiated. The positive impact of DFDI on GTFP, GTC, or GEC is confirmed, and the significance level of its impact on GTC or GEC decreases after adding control variables. Thus, Hypothesis 4 is also substantiated. The results of models (4), (5), and (6) are as follows.

The regression results for GTFP show that the manufacturing industry's IFDI, OFDI, Tsge, Gov, and ownership structure (d2) are negatively correlated with GTFP. In contrast, DFDI, Tsgx, institutional quality (d1), and material capital per labor (d3) are positively correlated with GTFP. Specifically, a 1% increase in the manufacturing industry's IFDI, OFDI, Tsge, Gov, and ownership structure (d2), respectively, results in negative growth in GTFP of 0.0926%, 0.0618%, 0.8233%, 0.0533%, and 0.1113%. Meanwhile, a 1% increase in DFDI, Tsgx, institutional quality (d1), and material capital per labor (d3), respectively, leads to positive growth in GTFP of 0.1802%, 0.7860%, 0.1433%, and 0.2493%. This indicates that unilaterally increasing the manufacturing industry's IFDI or OFDI significantly hinders the increase in the industry's GTFP, while DFDI has a significant promotional effect on GTFP.

The regression results for GTC show that the manufacturing industry's IFDI, OFDI, DFDI, Tsge, institutional quality (d1), ownership structure (d2), and material capital per labor (d3) have positive coefficients for GTC. Tsge has a significant positive effect on GTC at the 1% level. OFDI and ownership structure (d2) also have a significant positive effect on the GTC of the manufacturing industry at the 5% level. However, the impact of IFDI and DFDI on GTC in the manufacturing industry is not significant, indicating that increasing IFDI, OFDI, and DFDI improves the GTC of the manufacturing industry. Tsgx and Gov are negatively correlated with GTC in the manufacturing industry, suggesting that excessively optimizing the industrial structure and excessive Gov significantly inhibit GTC in the manufacturing industry.

Regression results for GEC show that the manufacturing industry's IFDI, OFDI, Tsge, Gov, and ownership structure (d2) are negatively correlated with GEC. In contrast, DFDI, Tsgx, institutional quality (d1), and material capital per labor (d3) are positively correlated with GEC, consistent with the direction of their effects on the manufacturing industry's GTFP. IFDI, OFDI, Tsge, and ownership structure (d2) significantly hinder GEC at the 1% level. Tsgx and institutional quality (d1) also significantly promote GEC at the 1% level, with DFDI significantly promoting GEC at the 5% level. This indicates that Tsgx, institutional quality (d1), and DFDI significantly improve GEC in the manufacturing industry.

4.2. Robustness Test

To prevent sample data from affecting estimates of GTFP and its decomposition anomalies in the manufacturing sector, this study excludes outliers from all sample data. In practice, the methodology adopted in this paper to remove anomalous data on GTFP, GTC, and GEC is to exclude data below the 5th percentile or above the 95th percentile of the mean. Then, the sample is re-estimated. The results of this estimation are shown columns (1)–(3) in Table 4.

According to the robustness test results from columns (1)–(3) in Table 4, after removing outliers in the manufacturing industry's GTFP, GTC, and GEC and re-analyzing the impact of IFDI, OFDI and DFDI on GTFP, GTC, or GEC, the following findings were observed in China's manufacturing industry: IFDI has a significantly negative correlation with GTFP at the 1% level and OFDI has a significantly negative correlation with GTFP at the 10% level. DFDI has a significantly positive correlation with GTFP at the 1% level. IFDI and DFDI have a positive correlation with GTC, but not significant. OFDI has a significantly positive correlation with GTC at the 1% level. IFDI and DFDI of China's manufacturing industry have a positive correlation with GTC, yet it is not significant. OFDI has a significantly

positive correlation with GTC at the 1% level. IFDI and OFDI have a significantly negative correlation with GEC at the 1% level, while DFDI has a significantly positive correlation with GEC at the 1% level, which is only different from the results of the analysis with control variables in Table 3 in significance. In Table 4 (models 1–3) and Table 3 (models 4–6), the effect of IFDI, OFDI and DFDI on GTFP, GTC, or GEC is the same in that there is no change in the direction of the effect, and the difference is that the significance changes. The above study reaffirms the robustness of the model used in the previous section to analyze the impact of IFDI, OFDI and DFDI on GTFP, GTC, or GEC.

In addition, to further reduce the bias of statistical results caused by sample self-selection, different from the previous least squares estimation method, this paper also adopts the Bootstrap self-sampling method for parameter estimation, which can realize the distribution of an unbiased asymptotic total through repeatedly sampling the original sample several times, and therefore improves the validity and consistency of parameter estimation results [76] From columns (4)–(6) in Table 4, it can be found that the impact of IFDI, OFDI, and DFDI on GTFP, GTC, or GEC remains constant.

Table 4. Robustness test.

Variable	Excluding Outliers			Bootstrap Estimation		
	(1)	(2)	(3)	(4)	(5)	(6)
dlnIFDI	−0.057 **	0.055	−0.130 ***	−0.0962 ***	0.0392	−0.135 **
	(−2.55)	(1.63)	(−3.26)	(−2.97)	(0.81)	(−2.28)
dlnOFDI	−0.029 *	0.059 **	−0.113 ***	−0.0618 ***	0.0572 ***	−0.119 ***
	(−1.88)	(2.56)	(−4.05)	(−3.11)	(3.18)	(−4.49)
lnDFDI	0.126 ***	0.025	0.169 ***	0.180 **	0.0113	0.169 *
	(3.72)	(0.48)	(2.74)	(2.31)	(0.17)	(1.88)
Constant	1.679 ***	−0.611 **	2.573 ***	2.512 ***	−0.591	3.103 ***
	(8.24)	(−2.08)	(7.08)	(4.17)	(−1.64)	(4.83)
Controlled variable	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No	No
*R*2	0.641	0.148	0.439	0.641	0.148	0.476
N	420	420	420	448	448	448

Note: ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.3. Phase-Specific Estimation Results and Analysis of the Overall Manufacturing Industry

Since 2008, influenced by the global financial crisis, China has made efforts to curb investment and carried out trade protectionism. The analysis is divided into two phases, before and after 2008, to study the impact mechanisms of IFDI, OFDI, and DFDI on GTFP, GTC, or GEC. This section explores whether the phase-specific characteristics of bidirectional FDI affect their causal relationship.

From the estimation results in Table 5, the impact of IFDI, OFDI, and DFDI on GTFP, GTC, or GEC shows a phase-specific characteristic. Through comparative analysis of the two phases, differences in the impacts of IFDI, OFDI, and DFDI on GTFP, GTC, or GEC are mainly manifested in their significance levels. F-tests, LM tests, and Hausman tests indicate that the estimation results of the FE model are most efficient for the impacts of IFDI, OFDI, and DFDI on GTFP or GEC across both phases, while the RE model provides the most efficient estimation results for the impacts of IFDI, OFDI and DFDI on GEC. The FE model estimation results of the two stages show that the negative impact coefficient of IFDI on GTFP has become larger, the negative impact coefficient of OFDI on GTFP has become smaller, and the positive impact coefficient of DFDI on GTFP has also become smaller. This suggests that in the long term, IFDI and DFDI may inhibit the growth of the manufacturing industry's GTFP, while OFDI has a positive long-term effect on GTFP growth. The negative impact coefficient of IFDI on GEC has become larger, the negative impact coefficient of OFDI on GEC has become smaller, and the positive impact coefficient of DFDI on GEC has also become smaller. This indicates that IFDI and DFDI will have an inhibitory effect on the

changes in GEC in the long run, while OFDI will have a promoting effect on the changes in GEC. The RE model estimation results show that the negative impact coefficient of IFDI and DFDI on GTC has become larger, while the positive impact coefficient of OFDI on GTC has also become larger. This indicates that IFDI and DFDI will have an inhibitory effect on the changes in GTC, whereas OFDI will have a promoting effect on GTC changes in the long term.

Table 5. Phase-specific estimation results of the overall manufacturing industry.

Variable	2004–2008		2009–2020			
	FE	RE	FE	FE	RE	FE
	lnGTFP	lnGTC	lnGEC	lnGTFP	lnGTC	lnGEC
dlnIFDI	−0.070	−0.012	−0.115	−0.121 ***	−0.017	−0.142 **
	(−1.54)	(−0.28)	(−1.13)	(−2.92)	(−0.29)	(−2.06)
dlnOFDI	−0.116 ***	0.053	−0.291 ***	−0.065 **	0.055	−0.132 ***
	(−3.33)	(1.30)	(−3.69)	(−2.38)	(1.43)	(−2.93)
lnDFDI	0.468 ***	−0.095	1.145 ***	0.109 **	−0.114 **	0.302 ***
	(3.04)	(−0.67)	(3.29)	(2.42)	(−2.13)	(4.06)
Constant	3.654 ***	−0.005	4.089 ***	3.672 ***	0.889 ***	3.120 ***
	(9.71)	(−0.01)	(4.80)	(12.11)	(2.79)	(6.36)
Controlled variable	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean VIF	3.55	3.55	3.55	2.89	2.89	2.89
F-value	31.77 ***		12.16 ***	25.06 ***		18.98 ***
Wald value		24.40 **			49.39 ***	
*R*2	0.792		0.593	0.454		0.387
F-test	21.08 ***		8.65 ***	37.51 ***		35.23 ***
LM Test		24.24 ***			620.85 ***	
Hausman Test	66.84 ***		45.03 ***	88.94 ***		60.67 ***
D-M Test	0.231		0.106	0.002		0.004
N	112	112	112	308	308	308

Note: *** and ** indicate significance at the 1% and 5% levels, respectively.

4.4. Estimation Results and Analysis of the Overall Manufacturing Industry by Industry Type

Further analysis compares the impact effects of IFDI, OFDI and DFDI on the GTFP and their decomposition in different types of manufacturing industries. The regression results as shown in Tables 6–8 indicate significant differences in the impact of IFDI, OFDI, and DFDI on the GTFP, GTC or GEC in different types of manufacturing industries. The differences in the impact of IFDI, OFDI, and DFDI on the GTFP or GEC are only manifested in their significance levels, while the impact of IFDI, OFDI, and DFDI on GTC shows differences in directionality, significance, and model selection in different types of manufacturing industries. Therefore, Hypothesis 2 is substantiated.

Regarding the estimation results for different technology industries, based on the classification method referenced by Fu et al. [77], the manufacturing industry is divided into high-tech manufacturing, mid-tech manufacturing, and low-tech industries. Then, high-tech and mid-tech industries are combined to form mid–high-tech and low-tech industries for analysis.

The regression results of China's low-tech manufacturing industries in Table 6 show that IFDI has a significantly negative correlation with GTFP at the 1% level, a negative correlation with GTC (but not significantly), and a significantly negative correlation with GEC at the 10% level. OFDI has a significantly negative correlation with GTFP at the 5% level, a positive correlation with GTC (but not significantly), and a significantly negative correlation with GEC at the 10% level. DFDI has a significantly positive correlation with GTFP at the 1% level, a positive correlation with GTC (but not significantly), and a significantly positive correlation with GEC at the 10% level.

Table 6. Estimated results for industries classified by technology.

Variable	Low-Tech Industries			Mid–High-Tech Industries		
	FE	RE	FE	FE	FE	FE
	lnGTFP	lnGTC	lnGEC	lnGTFP	lnGTC	lnGEC
dlnIFDI	−0.099 ***	−0.013	−0.098 *	−0.101 **	0.119 *	−0.220 ***
	(−2.81)	(−0.29)	(−1.84)	(−2.34)	(1.66)	(−2.72)
dlnOFDI	−0.068 **	0.022	−0.088 *	−0.059 ***	0.091 ***	−0.1450 ***
	(−2.22)	(0.54)	(−1.92)	(−2.84)	(2.66)	(−3.86)
lnDFDI	0.232 ***	0.068	0.161 *	0.174 ***	−0.060	0.234 **
	(3.64)	(0.91)	(1.69)	(3.40)	(−0.70)	(2.43)
Constant	3.749 ***	−0.240	4.064 ***	1.912 ***	−0.916 **	2.828 ***
	(8.68)	(−0.42)	(6.27)	(7.42)	(−2.14)	(5.85)
Controlled variable	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No	No
Mean VIF	3.64	3.64	3.64	3.24	3.24	3.24
F-value	48.97 ***		27.77 ***	44.20 ***	5.30 ***	18.43 ***
Wald value		29.29 ***				
*R*2	0.720		0.594	0.633	0.171	0.418
F-test	40.68 ***		39.05 ***	44.89 ***	16.01 ***	29.67 ***
LM Test		318.03 ***				
Hausman Test	100.98 ***		22.17 **	76.90 ***	18.32 **	59.23 ***
D-M Test	0.190		0.996	0.034	0.012	0.026
N	192	192	192	256	256	256

Note: ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The regression results of China's mid–high-tech manufacturing industries in Table 6 show that IFDI has a significantly negative correlation with GTFP at the 5% level, a significantly positive correlation with GTC at the 10% level, and a significantly negative correlation with GEC at the 1% level. OFDI has a significantly negative correlation with GTFP at the 1% level, a significantly positive correlation with GTC at the 1% level, and a significantly negative correlation with GEC at the 1% level. DFDI has a significantly positive correlation with GTFP at the 1% level, a positive but not significant correlation with GTC, and a significantly positive correlation with GEC at the 5% level.

Compared to low-tech industries, regarding the inhibitory effect of IFDI on GEC of mid–high-tech industries increases, its role in promoting GTC turns positive, but it ultimately increases its inhibitory effect on GTFP. The inhibitory effect of OFDI on GEC of mid–high-tech industries also increases, while its role in promoting GTC increases, ultimately weakening its inhibitory effect on GTFP. The promotional effect of the interactive development level of bidirectional FDI on GEC of mid–high-tech industries increases, while its effect on GTC turns inhibitory, ultimately weakening its promotional effect on GTFP.

Regarding the estimation results for different environmental types of industries, based on the classification method from Wang et al. [78], the manufacturing industry is divided into clean manufacturing and pollution-oriented manufacturing sectors.

The regression results of China's clean manufacturing industries in Table 7 show that IFDI has a significantly negative correlation with GTFP at the 1% level, a positive but not significant correlation with GTC, and a significantly negative correlation with GEC at the 5% level. OFDI has a significantly negative correlation with GTFP at the 10% level, a positive but not significant correlation with GTC, and a significantly negative correlation with GEC at the 5% level. DFDI has a significantly positive correlation with GTFP at the 1% level, a positive but not significant correlation with GTC, and a significantly positive correlation with GEC at the 10% level.

The regression results of China's polluting manufacturing industries in Table 7 show that IFDI has a significantly negative correlation with GTFP at the 10% level, a positive but not significant correlation with GTC, and a significantly negative correlation with GEC at

the 5% level. OFDI has a significantly negative correlation with GTFP at the 1% level, a positive but not significant correlation with GTC, and a significantly negative correlation with GEC at the 1% level. DFDI has a significantly positive correlation with GTFP at the 1% significance level and a positive but not significant correlation with GTC or GEC.

Table 7. Estimated results of industries classified by pollution level.

Variable	Clean Industry			Polluting Industry		
	FE	RE	FE	FE	FE	FE
	lnGTFP	lnGTC	lnGEC	lnGTFP	lnGTC	lnGEC
dlnIFDI	−0.099 ***	0.014	−0.145 **	−0.120 *	0.092	−0.212 **
	(−2.94)	(0.32)	(−2.56)	(−1.87)	(1.00)	(−2.25)
dlnOFDI	−0.050 *	0.045	−0.113 **	−0.057 ***	0.042	−0.099 ***
	(−1.75)	(1.20)	(−2.37)	(−3.12)	(1.60)	(−3.69)
lnDFDI	0.169 ***	0.056	0.184 *	0.140 ***	0.075	0.065
	(2.72)	(0.77)	(1.76)	(3.23)	(1.20)	(1.02)
Constant	3.512 ***	0.280	3.482 ***	1.356 ***	−0.713 **	2.070 ***
	(9.46)	(0.66)	(5.60)	(5.65)	(−2.06)	(5.87)
Controlled variable	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No	No
Mean VIF	3.28	3.28	3.28	4.86	4.86	4.86
F-value	49.78 ***		25.59 ***	45.02 ***	11.71 ***	21.10
Wald value		31.42 ***				
*R*2	0.646		0.484	0.722	0.403	0.549
F-test	37.67 ***		33.70 ***	38.12 ***	6.71 ***	31.69 ***
LM Test		615.95 ***				
Hausman Test	112.62 ***		51.95 ***	68.73 ***	49.87 ***	71.70 ***
D-M Test	0.021		0.523	0.116	1.5×10^{-10}	1.2×10^{-5}
N	272	272	272	176	176	176

Note: ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Compared with clean industries, the inhibitory effect of IFDI on GEC of polluting industries increases, and its role in promoting GTC also increases, ultimately increasing its inhibitory effect on GTFP. The inhibitory effect of OFDI on GEC of polluting industries weakens, and its role in promoting GTC also weakens, ultimately strengthening its inhibitory effect on GTFP. The promotional effect of DFDI on GEC of polluting industries weakens, and its role in promoting GTC increases, but ultimately, its promotional effect on GTFP weakens.

Regarding the estimated results for different resource-intensive industries, based on the classification by Wang et al. [78], the manufacturing industry is divided into labor-intensive and capital-intensive sectors.

The regression results of China's labor-intensive manufacturing industries in Table 8 show that IFDI has a negative but not significant correlation with GTFP, GTC, or GEC. OFDI has a significantly negative correlation with GTFP at the 5% level, a significantly positive correlation with GTC at the 10% level, and a significantly negative correlation with GEC at the 1% level. DFDI has a significantly positive correlation with GTFP at the 1% level, a negative but not significant correlation with GTC, and a significantly positive correlation with GEC at the 5% level.

The regression results of China's capital-intensive manufacturing industries in Table 8 show that IFDI has a significantly negative correlation with GTFP at the 1% level, a positive but not significant correlation with GTC, and a significantly negative correlation with GEC at the 1% level. OFDI has a significantly negative correlation with GTFP at the 1% level, a positive but not significant correlation with GTC, and a significantly negative correlation with GEC at the 1% level. DFDI has a significantly positive correlation with GTFP at the 1% level, a positive but not significant correlation with GTC, and a significantly positive correlation with GEC at the 1% level.

Table 8. Estimated results of industries classified by resource intensity.

Variable	Labor-Intensive Industries			Capital-Intensive Industries		
	FE	FE	FE	FE	RE	FE
	lnGTFP	lnGTC	lnGEC	lnGTFP	lnGTC	lnGEC
dlnIFDI	−0.133	−0.112	−0.022	−0.121 ***	0.038	−0.186 ***
	(−1.41)	(−0.82)	(−0.14)	(−4.84)	(1.13)	(−5.00)
dlnOFDI	−0.075 **	0.077 *	−0.152 ***	−0.059 ***	0.034	−0.109 ***
	(−2.58)	(1.85)	(−3.17)	(−2.67)	(1.12)	(−3.33)
lnDFDI	0.232 ***	−0.025	0.257 **	0.181 ***	0.020	0.230 ***
	(3.41)	(−0.25)	(2.28)	(3.80)	(0.33)	(3.26)
Constant	2.931 ***	0.134	2.797 ***	2.260 ***	−0.723 **	3.502 ***
	(7.61)	(0.24)	(4.40)	(7.95)	(−1.99)	(8.31)
Controlled variable	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No	No
Mean VIF	2.34	2.34	2.34	5.23	5.23	5.23
F-value	55.93 ***	3.44 ***	29.62 ***	28.24 ***		17.25 ***
Wald value					74.17 ***	
*R*2	0.685	0.118	0.536	0.598		0.476
F-test	33.96 ***	11.96 ***	23.54 ***	39.73 ***		53.14 ***
LM Test					373.52 ***	
Hausman Test	104.82 ***	16.18 *	59.00 ***	74.50 ***		35.53 ***
D-M Test	0.155	0.367	0.954	0.004		1.7×10^{-5}
N	256	256	256	192	192	192

Note: ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Compared with capital-intensive industries, the inhibitory effect of IFDI on GEC of labor-intensive industries weakens, its role in promoting GTC shifts to an inhibitory effect, and ultimately, its inhibitory effect on GTFP strengthens. The inhibitory effect of OFDI on GEC of labor-intensive industries weakens, its role in promoting GTC increases, and ultimately, its inhibitory effect on GTFP strengthens. The promotional effect of DFDI on GEC of labor-intensive industries strengthens, while its effect on GTC shifts from promotional to inhibitory, ultimately increasing its promotional effect on GTFP.

5. Results and Discussion

This paper empirically analyzes the impact of IFDI, OFDI, and DFDI on GTFP, GTC and GEC of industrial enterprises above designated size in China's 28 manufacturing sub-industries from 2004 to 2020 by using panel data and GTFP modeling. In view of the non-equilibrium of the volume of the bidirectional FDI at different stages and the inputs and outputs of different manufacturing segments, this paper empirically tests the phase-specific characteristics and inter-industry differences in the effect of IFDI, OFDI and DFDI on the manufacturing industry's GTFP and its decomposition. All the research conclusions in this paper are summarized in Table 9. The research findings indicate that, first, the increase in IFDI, OFDI, and DFDI promotes the GTC of the manufacturing industry. Second, the more rational the manufacturing industry structure, the more significant the promotional effect of IFDI, OFDI, and DFDI on GTFP. Third, the impact of IFDI, OFDI, and DFDI on GTFP, GTC, or GEC in the long term are manifested in the following three dimensions. The inhibitory effect of IFDI on GTC, GEC, or GTFP intensifies, while the promotional effect of OFDI on these aspects rises. The promotional effect of DFDI on GEC or GTFP declines, with an increased inhibitory effect on GTC. Fourth, compared with low-tech manufacturing industries, the inhibitory effect of IFDI on GTFP in mid–high-tech industries is increasing, the inhibitory effect of OFDI on GTFP is weakening, and the promotional effect of DFDI on GTFP is weakening. Fifth, compared with clean manufacturing industries, the inhibitory effect of IFDI and OFDI in polluting industries on GTFP is increasing, the promotional effect of DFDI on GTFP or GEC is weakening, and the promotional effect of IFDI, DFDI on GTC

is increasing. Sixth, compared with capital-intensive industries, the inhibitory effect of IFDI and OFDI on the GTFP of labor-intensive industries strengthens, while the promotional effect of DFDI also increases. The inhibitory effect of IFDI on GEC of labor-intensive industries weakens. The effect of IFDI and DFDI on GTC of labor-intensive industries shifts from promotional to inhibitory. Therefore, to achieve a green transformation and enhance the quality of industrial development in China's manufacturing industry, it is necessary to continue increasing OFDI in the manufacturing industry, while the increase in IFDI should be based on the rationalization of the industrial structure of the manufacturing industry.

Table 9. Summary of the conclusions of this paper.

Type	Variables	Conclusion		
		GTC	GEC	GTFP
Overall manufacturing industry	IFDI	Positive impact	Negative impact	Negative impact
	OFDI	Positive impact	Negative impact	Negative impact
	DFDI	Positive impact	Positive impact	Positive impact
Comparative analysis of the two phases	IFDI	Larger negative impact	Larger negative impact	Larger inhibitory effect
	OFDI	Larger positive impact	Smaller negative impact	Smaller inhibitory effect
	DFDI	Larger negative impact	Smaller positive impact	Smaller promotional effect
Mid–high-tech industries compared to low-tech industries	IFDI	Positive impact	Larger negative impact	Larger inhibitory effect
	OFDI	Larger positive impact	Larger negative impact	Smaller inhibitory effect
	DFDI	Negative impact	Larger positive impact	Smaller promotional effect
Polluting industries compared with clean industries	IFDI	Larger positive impact	Larger negative impact	Larger inhibitory effect
	OFDI	Smaller positive impact	Smaller negative impact	Larger inhibitory effect
	DFDI	Larger positive impact	Smaller positive impact	Smaller promotional effect
Labor-intensive industries compared with capital-intensive industries	IFDI	Negative impact	Smaller negative impact	Larger inhibitory effect
	OFDI	Larger positive impact	Larger negative impact	Larger inhibitory effect
	DFDI	Negative impact	Larger positive impact	Larger promotional effect

To sum up, this paper takes China's manufacturing industry as the research object to verify the impact mechanism of bidirectional FDI on domestic manufacturing GTFP theoretically and empirically. The results show that IFDI significantly inhibits GTFP, which is contrary to the research conclusions of Wang [28], but supports the findings of Hu et al. [31] and Li and Fan [32] to some extent. OFDI significantly inhibits GTFP, which is contrary to the research conclusions of Wang et al. [40] but supports the findings of Li et al. [47] and Shen et al. [48] to some extent. DFDI significantly promotes GTFP, which is contrary to the research conclusions of Ren and Zuo [5] and Zhang et al. [57] but supports the findings of Wang et al. [4], Liu et al. [55] and He et al. [56] to some extent. IFDI has a significant promotional effect on GTC, which is contrary to the research conclusions of Wang et al. [9] but supports the findings of Shen and Gong [8] to some extent. OFDI has a significant promotional effect on GTC, which supports the findings of Ma et al. [14] to some extent. On this basis, this paper also verifies the heterogeneity of the above relationship in low-tech, mid–high-tech, clean, polluting, labor-intensive, and capital-intensive manufacturing industries, which can provide a targeted bidirectional FDI development reference according to the actual industry. This is one of the important application contributions of this study. Moreover, this paper further explores the phase-specific characteristic effect of bidirectional FDI on its GTFP, finding that OFDI can effectively weaken the inhibitory effects in the long run. This can help China's manufacturing industry to select targeted forms and paths to amplify the positive promotion effect of bidirectional FDI on GTFP and continue increasing OFDI in manufacturing and IFDI based on the rationalization of the industrial structure of the manufacturing sector to achieve the green transformation of China's manufacturing industry and enhance the quality of industrial development.

This paper provides a theoretical basis and policy reference for China to promote bidirectional FDI and improve GTFP in the manufacturing industry. Nonetheless, this study has the following limitations. First, because of the data limitations, the time span chosen in this study to examine the impact of bidirectional FDI on manufacturing GTFP is from

2004 to 2020, and the latest relationship after the pandemic cannot be analyzed. Second, the enterprise is the main element of bidirectional FDI, but due to the restricted database, we only conducted research through industry panel data, without exploring typical cases or conducting research. In future research, we will seek breakthroughs in these aspects.

Author Contributions: Conceptualization, Z.F.; methodology, H.H.; validation, Z.F.; formal analysis, H.H.; data curation, H.H.; writing—original draft preparation, H.H.; writing—review and editing, L.W.; funding acquisition, Z.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Fund of China (Grant No. 19AJY001).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original data presented in the study are openly available in the China National Bureau of Statistics (NBS) at www.stats.gov.cn (accessed on 30 May 2024) and the China Economic and Social Big Data Research Platform at https://data.cnki.net (accessed on 30 May 2024).

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Literature comparison.

Reference	Methods	Variables	Data	Conclusions
Ma et al., 2022 [14]	Dynamic panel model	Two-way FDI; GTFP	Period of 2003–2018; 30 provinces in China	Positive
Ahmed and Ibrahim, 2019 [52]	Static panel model	FDI inflows and outflows; economic growth	Period of 1980–2017; US, UK and France; Malaysia, Turkey and Iran	Negative or Positive
Fu and Lin, 2021 [7]	Static panel model	The interaction between FDI and OFDI; the quality of economic growth	Period of 2004–2017; 30 provinces in China	Positive
Gong and Liu, 2020 [54]	Dynamic panel model	The coordinated development level of two-way FDI; pollution emissions	Period of 2004–2015; 30 provinces in China	Negative
Liu et al., 2024 [55]	Spatial Durbin Model	The coordinated development level of two-way FDI; GTFP	Period of 2004–2021; 30 provinces in China	Positive
He et al., 2024 [56]	Intermediary effect model; threshold effect model	Two-way FDI coordination development; GTFP	Period of 2011–2020; 30 provinces in China	Positive
Zhang et al., 2023 [57]	Dynamic spatial panel model	The coordinated development of two-way FDI; GTFP	Period of 2003–2019; 30 provinces in China	Positive
Zhao and He, 2020 [72]	Static panel model	FDI and OFDI; price distortion	Period of 2003–2016; 28 industries segments in China	Positive
Liu et al., 2022 [73]	Static panel model	IFDI and OFDI; the degree of GVCE	Period of 2003–2014; 18 manufacturing industry segments in China and 32 countries	Positive
Xu et al., 2020 [75]	Static panel model	Two-way FDI interactive development; the manufacturing innovation capacity	Period of 2003–2017; 27 manufacturing industry segments in China	Positive

References

1. Qiu, S.L.; Wang, Z.L.; Geng, S.S. How do environmental regulation and foreign investment behavior affect green productivity growth in the industrial sector? An empirical test based on Chinese provincial panel data. *J. Environ. Manag.* **2021**, *287*, 112282. [CrossRef] [PubMed]
2. Sun, S.Q.; He, Q.Q. Foreign Direct Investment in Different Manufacturing Industry and its Effect on Environmental Quality: Pollution Heaven or Pollution Halo? *J. Shandong Univ. (Philos. Soc. Sci.)* **2018**, *2*, 90–100.
3. Fu, H.; Li, G.P.; Zhu, T. Carbon Emission of China's Manufacturing Industry: Industry Differences and Decomposition of Driving Factors. *Reform* **2021**, *5*, 38–52.

4. Wang, K.L.; Xue, M.L.; Zhao, B. Can the Coordinated Development of Two-way FDI Improve Green Total Factor Productivity-Based on the Perspective of Industrial Structure Upgrading. *Commer. Res.* **2022**, *5*, 46–57.
5. Ren, S.; Zuo, H. The Impact of Two-way FDI and Regional Innovation Efficiency on China's GTFP: Based on Provincial Panel Data. *Stat. Manag.* **2021**, *36*, 42–46.
6. Han, Y.H.; Li, Z.W.; Zhang, F.; Shen, C. Environmental effects of bidirectional FDI in China. *Resour. Sci.* **2019**, *41*, 2043–2058. [CrossRef]
7. Fu, Y.H.; Lin, J.W. Interaction Mechanism Between FDI and OFDI and the Improvement of Economic Growth Quality: Analysis Based on the Effect of Technological Progress in Narrow Sense and Resource Allocation. *China Soft Sci.* **2021**, *2*, 133–150.
8. Shen, K.T.; Gong, J.J. Environmental Pollution, Technical Progress, and Productivity Growth of Energy-intensive Industries in China-Empirical Study Based on ETFP. *China Ind. Econ.* **2011**, *12*, 25–34.
9. Wang, B.; Wu, Y.R.; Yan, P.F. Environmental Efficiency and Environmental Total Factor Productivity Growth in China's Regional Economies. *Econ. Res. J.* **2010**, *45*, 95–109.
10. Cai, X.; Zhao, X.; Jiang, C.; Zhang, L. China's foreign direct investments: Do they promote domestic green technology? *J. Policy Model.* **2024**, *46*, 60–74. [CrossRef]
11. Jie, S.J.; Ji, S.B.; Wen, X.H. OFDI Reverse Technology Spillovers and China's Technical Progress: Research Review and Prospects. *J. Int. Trade* **2013**, *8*, 161–169.
12. Kong, X.G.; Li, Z.Z.; Lei, X.; Bao, X.Z. Environmental regulation, outward foreign direct investment, and China's green total factor productivity. *Environ. Dev. Sustain.* **2024**. [CrossRef]
13. Chai, Q.C.; Zhang, N.N. Outward Direct Investment and Reverse Technology Spillovers in China: A Study on Industrial Variation. *J. Cent. Univ. Financ. Econ.* **2016**, *8*, 113–120.
14. Ma, G.C.; Yang, X.Z.; Xu, J. Two-way FDI Coordinated Development and Green Total Factor Productivity: Theoretical Framework and China's Evidence. *Inq. Econ. Issues* **2022**, *7*, 173.
15. Ouyang, Y.Y.; Yu, M.Z. Analysis of Industry Differences in Reverse Technology Spillovers from China's OFDI. *Inq. Econ. Issues* **2011**, *4*, 101–107.
16. Liang, W.H.; Liu, H. Mechanism and empirical study of outward foreign direct investment driving China's technological progress. *Inq. Econ. Issues* **2017**, *2*, 111–117.
17. Kacani, J.; Shaqiri, G. Emerging ICT clusters in the Western Balkans: A convergence model based on financial statement analysis. *J. Reg. Sci. Policy Pract.* **2024**, *16*, 12687. [CrossRef]
18. Li, M.; Jin, Z.L. International R&D, Absorptive Ability and Reverse Technology Spillover of OFDI: Empirical Evidence Based on Panel Data from China. *J. Int. Trade* **2011**, *10*, 124–136.
19. Gao, X.B.; Wang, L.W.; Kong, Q.X. Whether OFDI Reverse Technology Spillover Has "Threshold Condition"—Based on Regional and Industry Perspectives. *J. Int. Bus.* **2018**, *6*, 61–74+126.
20. Wang, H.; Wang, S.Q. FDI, Technical Efficiency and Total Factor Productivity Growth—An Empirical Study Based on the Panel Data of Manufacturing Industry in Jiangsu Province. *East Chin. Econ. Manag.* **2016**, *30*, 19–25.
21. Bacchiocchi, A.; Bellocchi, A.; Giombini, G. Green Investment Challenges in European Firms: Internal vs. External Resources. *Sustainability* **2024**, *16*, 496. [CrossRef]
22. Wan, P.B.; Yang, M.; Chen, L. How Do Environmental Technology Standards Affect the Green Transition of China's Manufacturing Industry-A Perspective from Technological Transformation. *Chin. Ind. Econ.* **2021**, *9*, 118–136.
23. Sheng, B.; Lü, Y. Impact of Foreign Direct Investment on China's Environment: An Empirical Study Based on Industrial Panel Data. *Soc. Sci. Chin.* **2012**, *5*, 54–75+205–206.
24. Fu, J.Y.; Hu, J.; Cao, X. Different Sources of FDI, Environmental Regulation and Green Total Factor Productivity. *J. Int. Trade* **2018**, *7*, 134–148.
25. Li, X.P.; Lu, X.X. International Trade, Pollution Industry Transfer and Chinese Industries'CO_2 Emissions. *Econ. Res. J.* **2010**, *45*, 15–26.
26. AL-Dahash, H.F.K.; Mohammed, R.K.; Al-Rubaye, M.; Hardman, M. Comprehensive evaluation of the foreign direct investment (FDI) opportunities in Iraq: The Karbala Cement Manufacturing Company as a case study. *Int. J. Constr. Manag.* **2024**, *24*, 573–585. [CrossRef]
27. Chai, Z.X. Utilizing Foreign Investment, Environmental constraint and TFP Growth of China's Industrial: Comparative Research Based on Malmquist Index and Malmquist-Luenberger Index. *J. Technol. Econ.* **2013**, *32*, 64–70.
28. Wang, Z.Y. How Does Foreign Capital Openness Affect Green Total Factor Productivity? *Rev. Econ. Manag.* **2021**, *37*, 138–149.
29. Wei, L.; Pan, A. Do Export and FDI Aggravate Environmental Pollution in Resources-based Cities?—An Empirical Analysis Based on Panel Data of 285 Prefecture Cities in China. *J. Nat. Resour.* **2016**, *31*, 17–27.
30. Poelhekke, S.; Van der Ploeg, F. Green havens and pollution havens. *World Econ.* **2015**, *38*, 1159–1178. [CrossRef]
31. Hu, Y.; Zhang, X.W.; Li, J. Export, Geography Conditions and Air Pollution. *Chin. Ind. Econ.* **2019**, *9*, 98–116.
32. Li, G.L.; Fan, X.X. Industrial Agglomeration, Foreign Direct Investment and Green Total Factor Productivity. *J. Nanjing Univ. Financ. Econ.* **2019**, *5*, 1–10.
33. Jia, N.S.; Han, Y.H.; Zou, J.H. Effects of Two-way FDI on Industrial Restructuring in China: Influence Mechanism and Empirical Test. *J. Int. Trade* **2014**, *11*, 109–120.

34. Buckley, P.J.; Clegg, J.; Wang, C. Is the relationship between inward FDI and spillover effects linear: An empirical examination of the case of China. *J. Int. Bus. Stud.* **2007**, *38*, 447–459. [CrossRef]
35. Lin, B.; Chen, Z. Does factor market distortion inhibit the green total factor productivity in China? *J. Clean. Product.* **2018**, *197*, 25–33. [CrossRef]
36. Dong, Y.D.; Xia, W.H. Foreign Direct Investment and Green Total Factor Productivity in China: An Empirical Study Based on the System GMM and Threshold Model. *Shanghai J. Econ.* **2022**, *8*, 94–106.
37. Blomström, M. Host country benefits of foreign investment. *NBER Work. Pap.* **1991**, *w3615*.
38. Sui, Y.H. Dual Outward Foreign Direct Investment and Trade Structure: Theory and Evidence from China. *Int. Bus.* **2010**, *6*, 66–73.
39. Guo, X.; Wang, J. Outward foreign direct investment, green financial development, and green total factor productivity: Evidence from China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 47485–47500. [CrossRef]
40. Li, Y.; Zhang, X.H.; Jin, C.X.; Huang, Q. The influence of reverse technology spillover of outward foreign direct investment on green total factor productivity in China's manufacturing industry. *Sustainability* **2022**, *14*, 16496. [CrossRef]
41. Li, M.; Liu, S.C. Regional differences and threshold effects of reverse technology spillovers from outward direct investment: A threshold regression analysis based on China's provincial panel data. *J. Manag. World* **2012**, *1*, 21–32.
42. Chen, F.Q.; Yu, X.D. Research on the Feedback Mechanism of Enterprise OFDI on Independent Innovation: Taking Wanxiang Group OFDI as an Example. *Financ. Trade Econ.* **2009**, *3*, 101–107.
43. Huawei serves more than 170 countries and regions around the world, with 65 percent of its revenue coming from abroad. *China News*, 14 July 2014. Available online: http://www.chinanews.com (accessed on 30 May 2024).
44. Wang, J.; Chen, J.; Li, R. Outward foreign direct investment and urban green productivity: Promote or inhibit? *Int. Rev. Econ. Financ.* **2023**, *88*, 516–530. [CrossRef]
45. Yang, S.D.; Han, X.F.; Song, W.F. Does OFDI Affect China Green TFP. *J. Shanxi Univ. Financ. Econ.* **2017**, *39*, 14–26.
46. Song, Y.; Hao, F.; Hao, X.; Gozgor, G. Economic policy uncertainty, outward foreign direct investments, and green total factor productivity: Evidence from firm-level data in China. *Sustainability* **2021**, *13*, 2339. [CrossRef]
47. Li, F.; Yu, C. OFDI and home country structural upgrading: Does spatial difference exist in China? *Emerg. Mark. Finance Trade* **2020**, *56*, 1532–1546. [CrossRef]
48. Shen, C.; Xin, Y.R.; Jia, N.S.; Feng, R. The Influence Mechanism of OFDI on Industrial Green Total Factor Productivity—Based on the Two-Stage Super-SBM-Malmquist Exponential Module. *Chin. J. Manag. Sci.* **2024**, *32*(05), 229–240.
49. Tan, F.; Wan, H.; Jing, X.J.; Niu, Z.Y. The impact of outward foreign direct investment on carbon emission toward China's sustainable development. *Sustainability* **2021**, *13*, 11605. [CrossRef]
50. Ye, C.S.; Shu, Y.W.; Luo, L.F. An Empirical Study of Influence of Two-Way FDI on Changes in Industrial Structure -An Exploration on the Path to Promoting High-Quality Development through High-Level Opening-up. *Southeast Acad. Res.* **2020**, *2*, 153–163+248.
51. Zhang, J.; Wang, B. OFDI, Industrial Structure Upgrading and Green Total Factor Productivity. *Oper. Res. Manag. Sci.* **2023**, *32*, 165–170.
52. Ahmed, Y.A.; Ibrahim, R.R. The impact of FDI inflows and outflows on economic growth: An empirical study of some developed and developing countries. *J. Raparin Univ.* **2019**, *6*, 129–155. [CrossRef]
53. Huang, L.Y.; Liu, D.D.; Xie, H.Q. Research on the Harmonious Development of Outward Foreign Direct Investment and Inward Foreign Direct Investment. *Chin. Ind. Econ.* **2018**, *3*, 80–97.
54. Gong, M.Q.; Liu, H.Y. The Influence of Two-way FDI Coordinated Development and Industrial Structure Evolution on Environmental Pollution in China. *J. Int. Trade* **2020**, *2*, 110–124.
55. Liu, Q.; Cheng, H.Q.; Shao, L.Q. Empirical study on the effects of coordinated development of two-way FDI on regional green transformation under the carbon peaking and carbon neutrality goals: Local and spatial spillovers. *Chin. Soft Sci.* **2024**, *2*, 104–112.
56. He, B.; Yu, X.X.; Ho, S.; Zhang, X.Y.; Xu, D. Does China's Two-Way FDI Coordination Improve Its Green Total Factor Productivity? *Pol. J. Environ. Stud.* **2024**, *33*, 173–183. [CrossRef] [PubMed]
57. Zhang, Z.H.; Tang, L.Z.; Sun, L. Two-way FDI Coordinated Development, Market Segmentation and Green Total Factor Productivity. *Commer. Res.* **2023**, *5*, 81–89.
58. Dunning, J.H. Internationalizing Porter's diamond. *Manag. Int. Rev.* **1993**, *33*, 7–15.
59. Cui, X.H.; Lin, M.Y. How does Foreign Direct Investment Affect the Green Total Factor Productivity of Enterprises? Empirical Analysis Based on Malmquist-Luenberger Index and PSM-DID Model. *Bus. Manag. J.* **2019**, *41*, 38–55.
60. Solow, R.M. Technical change and the aggregate production function. *Rev. Econ. Stat.* **1957**, *39*, 312–320. [CrossRef]
61. Hulten, C.; Bennathan, E.; Srinivasan, S. Infrastructure, externalities, and economic development: A study of the Indian manufacturing industry. *World Bank Econ. Rev.* **2006**, *2*, 291–308. [CrossRef]
62. Wang, B. Technology Spillovers of FDI Technical Progress and Technical Efficiency. *J. Quant. Technol. Econ.* **2010**, *27*, 93–103+117.
63. National Standard of the People's Republic of China GB/T 4754-2017 Replaces GB/T 4754-2011. Available online: https://www.stats.gov.cn/sj/tjbz/gjtjbz/202302/P020230213402699744172.pdf (accessed on 30 May 2024).
64. Chen, S.Y. Reconstruction of Sub-industrial Statistical Data in China (1980–2008). *Chin. Econ. Q.* **2011**, *10*, 735–776.
65. Chen, F.L.; Xu, K.N. Home Market Size and TFP of China's Manufacturing Sector. *Chin. Ind. Econ.* **2012**, *5*, 44–56.
66. Hui, N.; Yang, X. Digital economy drive and high-quality development of China's manufacturing industry. *J. Shaanxi Norm. Univ. (Philos. Soc. Sci. Ed.)* **2022**, *51*, 133–147.
67. Malmquist, S. Index numbers and indifference surfaces. *Trab. Estad.* **1953**, *4*, 209–242. [CrossRef]

68. Färe, R.; Grosskopf, S.; Norris, M.; Zhang, Z. Productivity growth, technical progress, and efficiency change in industrialized countries. *Am. Econ. Rev.* **1994**, *84*, 66–83.
69. Chung, Y.H.; Färe, R.; Grosskopf, S. Productivity and Undesirable Output: A Directional Distance Function Approach. *J. Environ. Manag.* **1997**, *51*, 229–241. [CrossRef]
70. Gu, J.J.; Zhao, Y.L. China's Overseas R&D Investment and Green and High-quality Development in China's Manufacturing. *J. Quant. Technol. Econ.* **2020**, *1*, 41–61.
71. Cheng, H.F.; Lu, J.J. The Empirical Analysis of Knowledge Capital Impact on Total Factor Productivity of Industrial Enterprises. *Econ. Res. J.* **2014**, *49*, 174–187.
72. Zhao, F.S.; He, Q. Can Two-way FDI Help to Improve Factor Price Distortions? Empirical Evidence from China's Manufacturing Industries. *J. Nanjing Univ. Financ. Econ.* **2020**, *1*, 51–63.
73. Liu, J.T.; Li, R.X.; Wang, Z.R. The Impact of Bidirectional FDI on the Embeddedness of China's Manufacturing Global Value Chain. *J. Manag.* **2022**, *35*, 1–16.
74. Han, Y.H.; Huang, L.X.; Wang, X.B. Do Industrial Policies Promote Industrial Structure Upgrading? Theory and Evidence from China's Development-oriented Local Government. *Econ. Res. J.* **2017**, *52*, 33–48.
75. Xu, L.; Tang, S.S.; Zhang, X.M. A research on innovation-driven effect of two-way FDI interactive development in the manufacturing industry. *Sci. Res. Manag.* **2020**, *41*, 26–39.
76. Si, D.K.; Li, X.L.; Zhao, Z.K. Non-financial Enterprises' Shadow Banking Business and Stock Price Crash Risk. *China Ind. Econ.* **2021**, *06*, 174–192.
77. Fu, Y.H.; Ye, X.S.; Wang, Z.X. The Selection of Technological Progress Path of Manufacturing Structure Optimization—An Empirical Analysis Based on Dynamic Panel Data Model. *Chin. Ind. Econ.* **2014**, *9*, 78–90.
78. Wang, Y.; Fan, Z.C.; Li, X.Z. Endowment Structure, R&D Innovation and Industrial Upgrading. *Chin. Ind. Econ.* **2022**, *9*, 5–23.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.