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The Impact of Economic Growth, FDI and Energy Intensity on China's Manufacturing Industry's CO₂ Emissions: An Empirical Study Based on the Fixed-Effect Panel Quantile Regression Model

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Abstract: Since the reform and opening-up, China's CO₂ emissions have increased dramatically, and it has become the world's largest CO₂ emission and primary energy consumption country. The manufacturing industry is one of the biggest contributors to CO₂ emission, and determining the drivers of CO₂ emissions are essential for effective environmental policy. China is also a vast transition economy with great regional differences. Therefore, based on the data of China's provincial panel from 2000 to 2013 and the improved STIRPAT model, this paper studies the impact of economic growth, foreign direct investment (FDI) and energy intensity on China's manufacturing carbon emissions through the fixed-effect panel quantile regression model. The results show that the effects of economic growth, FDI and energy intensity on carbon emissions of the manufacturing industry are different in different levels and regions, and they have apparent heterogeneity. In particular, economic growth plays a decisive role in the CO₂ emissions of the manufacturing industry. Economic growth has a positive impact on the carbon emissions of the manufacturing industry; specifically, a higher impact on high carbon emission provinces. Besides, FDI has a significant positive effect on the upper emission provinces of the manufacturing industry, which proves that there is a pollution paradise hypothesis in China's manufacturing industry, but no halo effect hypothesis. The reduction of energy intensity does not have a positive effect on the reduction of carbon emissions. The higher impact of the energy intensity of upper emission provinces on carbon emissions from their manufacturing industry, shows that there is an energy rebound effect in China's manufacturing industry. Finally, our study confirms that China's manufacturing industry has considerable space for emission reduction. The results also provide policy recommendations for policymakers.

Keywords: carbon emission; economic growth; energy intensity; FDI; panel quantile regression; China's manufacturing industry

1. Introduction

Global warming caused by carbon emissions has caused severe damage to the world's ecological environment [1]. China's carbon emissions have exceeded that of the United States in 2007, and has become the world's largest CO₂ emission emitter [2]. With the rapid development of China's economy and increasing improvement of people's living standards, a large amount of energy will inevitably be

consumed, resulting in a large number of carbon emissions [3]. China has made a lot of efforts to reduce carbon emissions. The Chinese government has committed that by 2030, China's carbon emission intensity will be reduced by 60%–65% compared with 2005 [4], and the proportion of non-fossil fuels in primary energy consumption will be increased to 20% [5], striving to reach peak carbon emission by 2030 [6]. Therefore, China's carbon emission actions are increasingly concerned by the world [7]. Moreover, China will still be in the process of industrialization for a long time in the future [8], and the industrial sector is the main source of China's energy consumption and carbon dioxide emissions. Therefore, it is of great significance to understand the driving factors of carbon dioxide emission in China's major industries.

As the engine of China's industrialization and the pillar of China's national economy, the manufacturing industry has maintained rapid development since the 1990s. It is an industry with high energy consumption and emissions, and one of the largest contributors to the growth of China's CO₂ emission [9]. Especially with the further development of China's reform and opening-up, China is becoming a "world factory" [10], and the sales revenue of manufacturing industry has increased from 459 billion yuan in 1990 to 98,793.9 billion yuan in 2015, with an average annual growth of 24% [11]. However, the rapid development of China's manufacturing industry has also accelerated environmental damage, especially coal will continue to be China's primary energy source for a long time in the future. Due to the backward technology level, the energy consumption of China's manufacturing industry accounts for about 60% of China's total energy consumption and more than 50% of its total CO₂ emission [12]. China's manufacturing industry will continue to expand, which will also lead to an increase in carbon dioxide emissions of China's manufacturing industry [13]. Therefore, it is of great significance to explore the influencing factors of carbon emission in China's major manufacturing industries.

The three most important and discussed variables related to carbon emissions are economic growth, foreign direct investment and energy efficiency [14–17]. Due to different analysis samples, different selection variables and different estimation methods, although a large number of studies have discussed the relationship between economic growth and carbon emissions, the existing research has not found consistent evidence about the impact of economic growth on CO₂ emission. The main reason is that the heterogeneity of distribution has been neglected in the past [18].

With the increasing importance of foreign direct investment (FDI), many researchers believe that only better practice and excellent knowledge can make transnational corporations gain a competitive advantage in foreign land, which is the reason for the productivity spillover and environmental spillover of FDI [19]. Many studies focused on the relationship between economic growth, environmental pollution and FDI inflows, but few studies discussed the relationship between CO₂ emission and FDI inflows [20], especially in China's manufacturing industry. Economic growth depends on more FDI inflows, which in turn may lead to increased CO₂ emissions. In fact, will increasing FDI investment from developing countries have an impact on the environment [21]? Who should be responsible for greenhouse gas emissions, the producer or consumer? These problems have aroused broad and intense debate all over the world. Furthermore, to attract a large number of foreign investments, developing countries often neglect environmental issues through loose regulatory mechanisms, which leads to the emergence of the pollution avoidance hypothesis. In particular, the relaxation of environmental regulations and standards may promote CO₂ emission caused by foreign direct investment [22]. However, when advanced technology and management concepts are introduced by foreign capital, or foreign capital flows to the tertiary industry, the overall carbon emissions will decrease, which leads to the emergence of the halo effect hypothesis. Therefore, it is necessary to study the impact of FDI on China's manufacturing carbon emissions.

Moreover, compared with total carbon emissions and per capita carbon emissions, energy intensity is a better indicator of a country's energy and economic performance, and an important indicator of China's international emission reduction commitment [23]. However, the impact of energy intensity on overall carbon emissions is also controversial. Especially in the context of sustainable development,

carbon emission reduction and economic development are significant for China. Therefore, the target of energy intensity reduction means reducing CO₂ emissions without damaging economic growth.

Against this background, many scholars have conducted in-depth investigation and research on the main factors affecting carbon emissions and their relationship from three perspectives: The relationship between carbon emissions and economic development, the relationship between carbon emissions and foreign direct investment and the relationship between carbon emissions and energy intensity.

A large number of studies have explored the relationship between carbon emissions and economic development. The environmental Kuznets curve (EKC) theory and decoupling analysis model are the hot spots of this kind of research [24]. EKC theory reflects the inverted U-shaped relationship between economic growth and income; that is, at the initial stage of economic development, environmental degradation will be stimulated, and then environmental quality will be improved with economic growth. Due to global warming, the existence of EKC theory has attracted great attention from scholars. For example, Narayan and Narayan [25] studied the relationship between economic growth and carbon emissions in 43 developing countries and found that EKC curves do not exist in all countries and regions. Dong et al. [26], based on panel data of carbon emission levels related to natural gas consumption in 30 provinces of China, checked whether the EKC curve exists. Shuai et al. [27] used EKC theory to judge the inflexion point of an EKC curve of 164 countries and regions and proved that the relationship between economic development and carbon emissions of 123 countries conforms to EKC theory. Decoupling analysis is another method to study the relationship between carbon emissions and economic growth, which originates from physics and is defined by the OECD as the relationship between economic growth and environmental degradation [28]. Compared with EKC theory, decoupling analysis has the advantages of simple calculation [29], easier understanding and operation [30], as well as effective identification of the real-time dynamic relationship between economic development and environmental degradation [31]. Many studies explored the relationship between carbon emissions and economic growth through decoupling analysis [32–34], especially the research on China's industrial sub-industries [35–37]. For example, Hardt et al. [34] conducted a study on the economic growth and carbon emissions of the UK's production sector from 1997 to 2013 using decoupling analysis, proving that the UK's economic growth and carbon emissions have been successfully decoupled.

For the relationship between carbon emission and foreign direct investment, from previous studies, FDI has a two-way impact on carbon emissions; that is, the pollution haven hypothesis and halo effect hypothesis [18,38–40]. For example, Ren et al. [38] tested the impact of FDI, trade opening, export, import and per capita income on CO₂ emissions through a GMM method based on industrial panel data, and the results proved the existence of the pollution paradise hypothesis. Hao and Liu [39] used a two-equation model to explore the relationship between FDI, foreign trade and China's CO₂ emission. The results confirmed the existence of the halo effect hypothesis.

From the perspective of the relationship between carbon emissions and energy efficiency, the International Energy Agency (IEA), the United Nations Intergovernmental Panel on Climate Change (IPCC), some countries and many scholars believe that energy efficiency is an effective strategy to reduce energy consumption and carbon emissions [41], while other scholars believe that the improvement of energy efficiency will lead to the increase of CO₂ emissions, which is the rebound effect of energy efficiency. The improvement of energy efficiency reduces the effective price of energy use and services, which may increase the demand for energy and its services, leading to an increase in total emissions [42]. For example, Wang and Wei [15] evaluated China's energy and emission efficiency based on the DEA method and measured its energy conservation and emission reduction potential. Yao et al. [43] discussed carbon emission efficiency, energy efficiency and emission reduction potential from a regional perspective, and found that there was significant group heterogeneity between carbon emission efficiency and energy efficiency in various regions of China. Lin and Zhao [44], based on the Morishima alternative elasticity (MES) model, through asymmetric energy price, cross logarithmic cost function and other methods, established a research framework to measure the rebound effect of China's

textile industry. The results show that improving energy efficiency is not the only way for China's textile industry to achieve energy conservation and emission reduction. Zhang et al. [42], based on the annual data of 1994–2012, studied the energy rebound effect of the industrial sector through an index decomposition model and panel data model. The results show that the energy rebound effect does exist in China's industrial industry, and the energy rebound effect of industrial industry and manufacturing industry shows an overall downward trend over time.

Although the above research has a great contribution to understanding the main factors affecting carbon dioxide emissions of China's manufacturing industry, it also has its limitations. First, the mitigation potential of China's total carbon dioxide emissions from manufacturing is still unclear at this stage [45]. Moreover, the analysis of the relationship between China's carbon emissions and economic growth, FDI and energy intensity is still lacking. Given this, it is necessary to clarify the factors that affect the carbon dioxide emissions of China's manufacturing industry, and make an effective and comprehensive analysis of the driving factors of the carbon emissions of China's manufacturing industry, so as to make up for the research gap of the relationship between the carbon emissions of China's manufacturing industry and China's economic development, FDI and energy intensity, and strive to enrich the research results of China's low-carbon economy at the industry level.

Compared with the traditional OLS method, the panel quantile method may provide more complete results, and prove the possible heterogeneity at the same time [46]. Meanwhile, many scholars employ the panel quantile method to study the relationship between carbon emissions and its influencing factors [9,18,46–49]. Besides, each quantile can fully describe the distribution characteristics of the carbon emissions of China's manufacturing industry. That is, the high quantile represents the provinces with high carbon emissions from the manufacturing industry, while the low quantile represents the provinces with low carbon emissions from the manufacturing industry. Therefore, based on the improved STIRPAT model and the panel quantile regression model with a two-way fixed effect, this paper uses the panel data of 2000–2013 to study the impact of FDI, economic growth and energy intensity on China's manufacturing carbon emissions. Each quantile can fully describe the distribution characteristics of carbon emissions of China's manufacturing industry. That is, the high quantile represents the provinces with high carbon emissions from the manufacturing industry, while the low quantile represents the provinces with low carbon emissions from the manufacturing industry. The results show that the impact of economic growth, foreign direct investment and energy intensity on the carbon emissions of the manufacturing industry is different under different levels of carbon emissions from the manufacturing industry and different regions, with obvious heterogeneity, and economic growth plays a decisive role in the carbon emissions of the manufacturing industry. Among them, economic growth has a positive impact on the carbon emissions of the manufacturing industry, and the higher the impact of the economic growth of high emission provinces on the carbon emissions of the manufacturing industry is, the more significant the impact of foreign direct investment is on the carbon emissions of the manufacturing industry and on regional heterogeneity. The impact is also more significant in high emission provinces and supports the hypothesis that there is a pollution paradise in China's manufacturing industry, but there is no halo effect hypothesis. In addition, the reduction of energy intensity does not have a positive effect on the reduction of carbon emissions. The higher the impact of energy intensity on the carbon emissions of the manufacturing industry in high emission provinces, the higher the impact of energy intensity on the carbon emissions of the manufacturing industry, indicating that there is an energy rebound effect in China's manufacturing industry. Finally, we have proven that China's manufacturing industry has considerable space for emission reduction. The novelties of this paper are fourfold: (1) This paper focuses on the carbon emissions of China's manufacturing industry. As reducing manufacturing's carbon emissions plays a crucial role in China's response to climate change, studying the impact of economic development, foreign direct investment and energy efficiency on China's manufacturing carbon emissions will help us better understand the importance of industry emission reduction and provide a new perspective for policymakers to reduce overall carbon emissions. (2) We thoroughly study the determinants of CO₂ emission of the Chinese

manufacturing industry with distribution heterogeneity. This is mainly because to effectively achieve reducing manufacturing's emissions will require full consideration of the spatial differences in different regions and the differential effects of various variables in different periods [47,50]. China is currently facing economic transformation, with substantial regional differences. In this context, if cross-regional heterogeneity is not considered, the calculation results of energy and carbon emission variables may be biased. Specifically, China has many provinces, and the level of economic development, natural resources, technology and human capital of each province are different. (3) Fixed-effect panel quantile regression model can provide more information and data, which provides a new perspective on how these factors affect the carbon emissions of China's manufacturing industry, and then helps decision-makers to make more strict environmental protection policies. The regression coefficients of different quantiles are often different; that is, the impact of explanatory variables on carbon emissions of the manufacturing industry in different quantiles is different. The quantile regression model can describe the full conditional distribution of dependent variables. Therefore, it can help us to understand more comprehensively the factors related to China's manufacturing industry's carbon emissions, especially in extreme distribution conditions. (4) Our model contains some related control variables, which can solve the problem of variable deviation ignored in previous studies [51].

2. Methodology and Data

2.1. Fixed-Effect Panel Quantile Regression

This paper discusses the effects of economic growth, foreign direct investment and energy efficiency on China's manufacturing industry's carbon emissions through the fixed-effect panel quantile regression model. Traditional OLS usually leads to the underestimation or overestimation of the correlation coefficient, and even cannot detect its relationship [52]. However, by using panel quantile regression, we can study the determinants of China's manufacturing industry's carbon emissions over the entire conditional distribution, especially those regions with the most and least emissions. The quantile regression method is the extension of the mean regression on other quantiles, which was first proposed by Koenker and Bassett [53]. Based on different quantile points, it makes full use of sample data for regression analysis. The quantile regression model has been widely used in environmental research [18,46,47,49,54]. The conditional quantile y_i for a given x_i is as follows:

$$Q_{y_i}(\tau|x_i) = x_i^T \beta_\tau \quad (1)$$

The traditional quantile regression model is robust to outliers, but the traditional model does not take into account the heterogeneity that cannot be observed in any province. Therefore, to better control the non-observed heterogeneity of individual provinces, this paper uses the panel quantile model with a fixed effect to estimate the conditional heterogeneity covariance effect of carbon emission drivers in China's manufacturing industry, so as to control the non-observed individual heterogeneity [55–57]. The quantile regression model of fixed effect panel is as follows:

$$Q_{y_{it}}(\tau_k|\alpha_i, x_{it}) = \alpha_i + x_{it}'\beta(\tau_k). \quad (2)$$

However, the fixed-effect panel quantile regression model has its disadvantages; that is, the total experience containing a large number of fixed effects (α_i) is affected by the additional parameters [58]. However, if the number of individuals tends to infinity because the number of observations per unit cross-section is fixed, the estimators will be inconsistent. In particular, the method of eliminating the fixed effect that cannot be observed is unfeasible in the quantile regression model. The main reason is that the expectation is a linear operation, but the conditional quantile is not [57]. To solve these problems, Koenker [59] proposed to estimate the covariate effect in different quantiles by taking the fixed effect that cannot be observed as a parameter. A penalty term is introduced in the process of

minimizing the benefits of this method, which solves the problem of parameter quality estimation. The calculation method of parameter estimation is as follows:

$$\min_{(\alpha, \beta)} \sum_{k=1}^K \sum_{t=1}^T \sum_{i=1}^N \omega_k \rho_{\tau_k}(y_{it} - \alpha_i - x_{it}^T \beta(\tau_k)) + \lambda \sum_i |\alpha_i| \quad (3)$$

where $i (i = 1, 2, \dots, 30)$ is each province, t is the number of observations per province, K is the quantile, x is the explanatory variable matrix, ρ_{τ_k} is the quantile loss function and ω_k is the relative weight of the k -th quantile, which is used to control the contribution of the k -th quantiles to the fixed-effect estimation. The same as Lamarche [60] and Alexander [61], this paper uses the equal weight quantile, namely $\omega_k = 1/K$, and λ is the tuning parameter, which improves β estimation performance by reducing individual effects to zero. If λ is zero, then the penalty term disappears, and we get the usually fixed-effect estimator. On the contrary, when λ becomes infinite, we get an estimate of a model without any individual influence. Consistent with Damette and Delacote [62], this paper sets λ to 1.

2.2. Model Specification

The IPAT equation (Equation (4)) is used to study various factors leading to environmental pollution [63], which is defined as

$$I = P \times A \times T \quad (4)$$

where I represents the emission level of pollutants, P represents the population scale, A represents the richness of a country and T represents technological progress. Then, the IPAT equation cannot directly determine how various factors affect environmental change [64], and the elasticity of the three factors to environmental change is unified, which is contrary to the traditional EKC theory [65]. Therefore, to fully investigate the factors affecting environmental change, the STIRPAT model is as follows [66]:

$$I_t = a P_t^b A_t^c T_t^d e_t \quad (5)$$

where P , A and T have the same meaning as in Equation (4), a represents the intercepted item, and b , c and d represents the elasticity of environmental impact on P , A , T , t is the representative time and e_t is the random interference term. The development of the manufacturing industry is very important for the sustainable development of China's economy and environment. Therefore, it is necessary to study one of the important factors that influence the carbon emissions of the manufacturing industry. Besides, although FDI is regarded as one of the main driving forces of economic growth in many cases, it may also bring harm to the environment. An increase in FDI can not only lead to an increase in the manufacturing industry's carbon emissions through the improvement of technology and systems but also to the decrease of manufacturing's carbon emissions due to the transfer of high emission production lines. Therefore, it is necessary to study the relationship between FDI and manufacturing's carbon emissions. Moreover, energy intensity is also essential for the carbon dioxide emission levels of the iron and steel industry. The energy-saving potential of the manufacturing industry in the future is determined to some extent by energy intensity [67]. Therefore, energy intensity is also very important for the carbon emission level of the manufacturing industry. Furthermore, in order to fully understand the impact of economic growth, foreign direct investment and energy intensity on China's manufacturing industry's carbon emissions, based on the STIRPAT model, we introduce the total population, urbanization rate, foreign trade dependence and energy structure as control variables into the model according to the reality of China's manufacturing industry and relevant previous studies [9,50,68,69].

For the above reasons, based on the extended STIRPAT model (logarithmic form), this paper constructs the fixed-effect panel quantile regression model of China's manufacturing industry and

studies the impact of economic growth, FDI and energy efficiency on China's manufacturing industry's carbon emissions. The conditional quantile function of quantile τ is as follows:

$$Q_{CO_2_{it}}(\tau|\alpha_i, x_{it}, \xi_t) = \alpha_i + \beta_{1\tau}POP_{it} + \beta_{2\tau}GDP_{it} + \beta_{3\tau}FDI_{it} + \beta_{4\tau}URB_{it} + \beta_{5\tau}FTD_{it} + \beta_{6\tau}ENE_{it} + \beta_{7\tau}ENS_{it} + \xi_t \quad (6)$$

where the introduction of variables is shown in Table 1 and i and t have the same meaning as in Equation (3). All variables are transformed into their natural logarithm forms.

Table 1. Definition of variables.

Variable	Definition	Unit
CO ₂	Total carbon emissions from the manufacturing industry	Ten thousand tons
POP	Total population	Ten thousand people
GDP	Per capita GDP	Yuan
FDI	Amount of foreign direct investment	100 million
URB	Urbanization rate	%
FTD	The ratio of dependence on foreign trade	%
ENE	Energy intensity	%
ENS	Energy structure	%

Note: (1) All data are annual data from 2000 to 2013. (2) Due to the lack of data, Tibet is not included. (3) Per capita GDP is based on the year 2000.

2.3. Variable, Data Description and Descriptive Statistic

2.3.1. Variable Description

The purpose of this paper is to explore the impact of economic growth, foreign direct investment and energy efficiency on China's manufacturing industry's carbon emissions using data from 30 provinces (excluding Tibet, Hong Kong and Macao, China) from 2000 to 2013. As the relationship between economic growth, foreign direct investment, energy intensity and manufacturing's carbon emissions may be affected by other relevant factors [18] (thus, in order to further analyze the influencing factors of the manufacturing industry's carbon emissions), based on previous literature, we expanded the STIRPAT model [70–72], which includes population size, urbanization rate, dependence on foreign trade and energy structure. The population scale is the total number of each province; according to the regulations of the National Bureau of Statistics of China, the urbanization rate is defined as the ratio of urban population to total population; the dependence on foreign trade is the ratio of total import and export to GDP. Based on the exchange rate between China and the United States over the years, we calculate the dependence on foreign trade of each province; the energy structure is the coal consumption of manufacturing industry divided by its total energy consumption. All variables were converted to the natural logarithm before empirical analysis. See Table 1 for details of data variables.

2.3.2. Data Description

Table 2 shows the descriptive statistics of all variables. When the data samples have a non-normal distribution, the quantile regression estimation results are more robust than OLS. It can be seen from Table 3 that, based on the results of skewness and kurtosis, we find that the distribution of all variables is skewed, and its distribution is more concentrated than the normal distribution of the long tail. Therefore, compared with OLS, the quantile regression model is more reasonable for empirical analysis, and the estimation of the regression coefficient is more robust.

Table 2. Descriptive statistical analysis.

Variable	CO ₂	POP	GDP	FDI	URB	FTD	ENE	ENS
Min.	520.10	516.50	263.70	1.27	0.23	0.00	0.03	0.07
Median	7214.50	3823.50	5442.80	171.45	0.45	0.13	0.6148	0.71
Mean	13,983.50	4344.80	7751.70	331.42	0.48	0.32	0.9027	0.72
Max.	253,302.10	10,644.00	46,522.70	2257.32	0.90	6.77	7.1515	1.87

Table 3. Normal distribution test.

Variable	LCO ₂	LPOP	LGDP	LFDI	LURB	LFTD	LENE	LENS
Std. Dev.	21,836.31	2641.90	7522.12	419.33	0.15	0.57	1.03	0.24
Skewness	6.77	0.49	2.14	1.98	1.02	6.84	3.23	1.62
Kurtosis	65.434	2.32	8.60	6.88	3.76	70.89	16.06	10.53
Jarque–Bera	71,422.42	24.79	867.99	538.67	82.71	83,926.19	3712.26	1176.45

3. Empirical Results and Analysis

In this section, we first conduct the panel unit root test on the research samples and then perform the panel unit root test. Finally, the panel quantile model is used to study the impact of economic growth, FDI and energy intensity on China's manufacturing industry's carbon emissions.

3.1. Panel Unit Root Test and Panel Cointegration Results

Because of the complexity of real economic phenomena, the data of the economic variables are usually non-stationary. If we use non-stationary data for regression estimation analysis, it will lead to the emergence of pseudo regression [73]. Therefore, before estimating the panel quantile regression model, we tested whether the variables used in the model are stable. In this paper, four-panel unit root tests were carried out, i.e., the LLC test, IPS test, Fisher ADF test and Fisher PP test. Table 4 shows the results of panel unit root test. These results show that the original hypothesis of unit root can be rejected by all the selected variables. At the 1% level, the unit root zero hypothesis of all variables can be rejected almost completely for the first difference variable. Therefore, all variables can be analyzed directly without a difference.

Table 4. Panel unit root test results.

Variable	CO ₂	POP	GDP	FDI	URB	FTD	ENE	ENS
Levels								
LLC	−6.58 *** (1.85)	−2.22 ** (−1.88 **)	−11.07 *** (2.22)	−3.45 *** (−14.33 ***)	−5.21 *** (−5.36 ***)	−6.55 *** (−6.25 ***)	9.99 (2.05)	4.96 (3.52)
IPS	−0.54 (2.59)	5.12 (1.91)	−0.53 (2.28)	1.23 (−4.32 ***)	3.23 (0.72)	−2.09 ** (0.01)	7.81 (7.02)	7.34 * (2.79)
Fisher-ADF	77.98 * (48.178)	36.65 (54.43)	87.38 ** (40.36)	55.32 (107.87 ***)	46.46 (50.06)	81.20 ** (59.01)	16.59 (16.03)	24.66 (46.70)
Fisher-PP	147.91 *** (95.70 ***)	66.69 (65.19)	28.97 (94.95 ***)	59.98 (95.52 ***)	207.46 *** (42.96)	64.49 (47.30)	23.33 ** (39.68 **)	42.42 (68.16)
First difference								
LLC	0.99 (1.16)	2.27 (8.44)	−2.84 *** (−5.37 ***)	−13.41 *** (−9.05 ***)	−5.51 *** (−5.18 ***)	−10.02 *** (−11.19 ***)	−0.25 (−0.85)	−2.82 *** (−1.11)
IPS	−2.02 ** (−1.21)	0.33 (3.32)	−1.96 ** (1.72)	−8.36 *** (−4.37 ***)	−2.90 *** (−1.58 *)	−6.60 *** (−5.47 ***)	−1.24 ()	−3.86 *** (−2.34 ***)
Fisher-ADF	82.26 ** (69.14)	63.09 (41.79)	76.61 * (55.02)	180.51 *** (122.51 ***)	89.62 *** (79.12 **)	149.52 *** (136.52 ***)	72.31 (88.32 **)	110.45 *** (90.31 ***)
Fisher-PP	184.96 *** (191.37 ***)	147.60 *** (72.59)	78.50 * (89.54 ***)	265.62 *** (243.24 ***)	146.01 *** (180.17 ***)	233.39 *** (292.67 ***)	240.78 *** (387.93 ***)	262.04 *** (269.53 ***)

Note: (1) LLC (Levin, Lin and Chu) and IPS (Im, Pesaran and Shin W-stat) represent the panel unit root test by Levin et al. [74]. Fisher-ADF (ADF-Fisher Chi-square) and Fisher-PP (PP-Fisher Chi-square) represent the panel unit root test on behalf of Maddala and Wu [73]. (2) Numbers without brackets are individual intercept values. (3) The numbers in brackets are individual intercept and trend values. (4) *** represents statistical significance at the 1% level, ** represents statistical significance at the 5% level, and * represents statistical significance at the 10% level.

The panel cointegration test is employed to judge whether there is a long-term equilibrium relationship among variables. Pedroni's [75,76] panel cointegration test and Kao's [77] panel cointegration test are widely used to test the existence of panel cointegration. On this basis, and thus in order to have comparative analysis, we used the Pedroni panel cointegration test method and Kao panel cointegration test method to verify Equation (6). The Pedroni and Kao tests are both based on the regression residual under the condition of the independent section. It can be seen from Table 5 that there is a cointegration relationship between variables. Therefore, we took all variables directly into the equation for quantile regression.

Table 5. Panel co-integration test results of Pedroni and Kao.

Pedroni Cointegrating Vector Test: Panel Specific			Kao Residual Cointegration Test		
Test Value	Statistic	p-Value		t-Statistic	Prob.
Modified Phillips–Perron t	8.77	0.00	ADF	−6.72	0.00
Phillips–Perron t	−14.90	0.00	Residual variance	0.02	
Augmented Dickey–Fuller t	−13.13	0.00	HAC variance	0.02	

3.2. Panel Quantile Regression Results

As each quantile can adequately describe the distribution characteristics of manufacturing's carbon emissions, the quantile regression model directly reveals the marginal effect of explanatory variables on manufacturing carbon emissions at different quantile levels. Besides, China's manufacturing industry has obvious characteristics of massive development, and there are significant differences in different provinces, mainly ignoring the fixed effect of time cycle that may lead to the deviation of estimates in traditional time series research. Therefore, in order to control the heterogeneity of distribution and consider the different effects of different periods, this paper adopts a panel quantile model with bidirectional fixed effects [60] for regression analysis. Table 6 presents the panel quantile regression estimates of the two-way fixed effect (5th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, 90th and 95th quantiles). In general, the influence of various factors and different quantiles on carbon emissions is different. The quantile results show that economic growth (*GDP*), foreign direct investment (*FDI*) and energy intensity (*ENE*) have different effects on manufacturing's carbon emissions under different levels and regions.

Table 6. Panel quantile regression results.

Variable	Quantile Statistics									
	5th	20th	30th	40th	50th	60th	70th	80th	90th	95th
Constant	3.45 *** (3.31)	3.67 *** (3.81)	3.74 *** (3.89)	3.69 *** (3.89)	3.88 *** (4.11)	3.94 *** (4.17)	3.91 *** (4.03)	3.92 *** (4.02)	3.84 *** (3.81)	3.56 *** (3.48)
POP	0.08 (0.35)	0.08 (0.52)	0.05 (0.33)	0.01 (0.08)	−0.01 (−0.02)	−0.05 (−0.25)	−0.11 (−0.56)	−0.18 (−0.90)	−0.24 (−1.16)	−0.27 (−1.34)
GDP	0.59 *** (2.80)	0.57 *** (4.83)	0.59 *** (4.92)	0.63 *** (5.08)	0.64 *** (4.70)	0.69 *** (4.53)	0.73 *** (4.59)	0.79 *** (4.91)	0.84 *** (5.19)	0.90 *** (5.50)
FDI	0.07 (1.26)	0.08 (1.35)	0.06 (1.04)	0.05 (1.01)	0.03 (0.66)	0.01 (0.28)	0.04 (0.74)	0.05 (0.77)	0.09 (1.41)	0.13 * (1.89)
URB	0.65 (1.25)	0.72 ** (1.99)	0.65 * (1.76)	0.57 (1.53)	0.61 (1.57)	0.62 (1.55)	0.48 (1.18)	0.43 (1.05)	0.25 (0.64)	0.15 (0.37)
FTD	0.05 (1.15)	0.01 (0.31)	0.01 (0.23)	0.01 (0.23)	0.01 (0.17)	0.01 (0.19)	0.01 (0.24)	0.00 (0.09)	0.02 (0.43)	0.04 (0.90)
ENE	0.27 *** (3.00)	0.28 *** (3.61)	0.28 *** (3.56)	0.28 *** (3.60)	0.29 *** (3.76)	0.29 *** (3.81)	0.29 *** (3.64)	0.30 *** (3.42)	0.42 *** (3.58)	0.50 *** (3.93)

Table 6. Cont.

Variable	Quantile Statistics									
	5th	20th	30th	40th	50th	60th	70th	80th	90th	95th
ENS	−0.31 (−1.40)	−0.32 (−1.53)	−0.35 * (−1.75)	−0.38 * (−1.94)	−0.43 ** (−2.19)	−0.46 ** (−2.44)	−0.46 ** (−2.47)	−0.48 ** (−2.42)	−0.57 *** (−2.72)	−0.66 *** (−3.39)

Note: (1) This table shows the results of the panel quantile regression model with carbon emissions of the manufacturing industry in different provinces as dependent variables and FDI, economic growth, energy intensity and control variables as independent variables. (2) The number in brackets are t values. (3) *** represents statistical significance at the 1% level, ** represents statistical significance at the 5% level, and * represents statistical significance at the 10% level.

4. Discussion

According to the above empirical results, there are some interesting phenomena.

In terms of economic growth, we can find that the impact of economic growth on carbon emissions of the manufacturing industry is not heterogeneous. The GDP coefficients of all quantiles are very significant (at the level of 1%), and their coefficients show a trend of decreasing first and then increasing. These results indicate that economic growth has a positive impact on carbon emissions of the manufacturing industry, which is consistent with the research conclusions of Xu et al. [50] and Lin and Xu [9]. The higher the impact of economic growth on the manufacturing industry's carbon emissions of high emission provinces, the stronger the impact of economic growth on manufacturing's carbon emissions of provinces in the 95th quantile than other quantile provinces. The reason may be that, at present, China mainly relies on fixed investment to promote economic growth, and the manufacturing industry, as an essential industry, plays a vital role in fixed investment. At the same time, the manufacturing industry is a high emission industry, and there is a significant demand for many products. The manufacturing industry not only promotes the economy but also produces a lot of emissions. Besides, China's production emissions are greater than its consumption emissions. Under the existing climate policy and international trade rules, carbon leakage occurs [78]. Although foreign trade is one of the power sources of China's economic growth, due to the low level of technology in China at this stage, most of the products exported are energy-intensive products. Therefore, while foreign trade causes economic growth, it also leads to an increase in carbon emissions in the manufacturing industry.

On the contrary, for FDI, we can observe that the FDI coefficient is positive at all quantile points (especially the impact is significantly positive in high emission provinces), but it is not significant at the 10% level except for the high quantile (i.e., 95th quantile, which is significant at 10%). These results support the hypothesis that the manufacturing industry is a pollution heaven in China, but not the halo effect hypothesis. The inflow of FDI will lead to an increase in carbon emissions in big emission provinces, but the impact on the low quantile point is not significant, which means that most FDI investment in small emission provinces may be located in the less-polluting manufacturing industry, and the environmental laws and regulations of low emission provinces may be relatively perfect and strict. Alternatively, with the help of its advanced production technology and management experience, it has a positive impact on the emissions of the manufacturing industry.

Similarly, in terms of energy intensity, we can find that the impact of energy intensity on the carbon emissions of the manufacturing industry is not heterogeneous. The *ENE* coefficient of all quantile points is very significant; that is, it is significant at the 1% level, and its coefficient shows a monotonous increasing trend. Compared with the low emission provinces, the energy intensity of the high emission provinces has a higher impact on the carbon emissions of their manufacturing industries. In particular, the impact of energy intensity on carbon emissions of the 95th quantile provinces is higher than that of other quantile provinces. Consistent with Du et al. [79] and Lin and Xu [9], the reduction of energy intensity does not have a positive effect on the reduction of carbon emissions. The research results show that there is a rebound effect of energy intensity in China's manufacturing industry, and our research results are consistent with the previous empirical study Zhang et al. [42], which also confirms that there

is indeed an energy rebound effect in China's manufacturing industry. Through the above studies, we find that for China's manufacturing industry, the current stage is too single to pursue the macro energy intensity goal, while ignoring the overall control of carbon emissions, which directly affects the energy-saving effect of the manufacturing industry, causing damage to the whole environment.

In addition, regardless whether in regions with high carbon emission or low carbon emission, the impact of economic growth on carbon emission of the manufacturing industry is far higher than that of foreign direct investment and energy intensity, which plays a decisive role, followed by energy intensity, because the *ENE* coefficient in each quantile is greater than the *FDI* coefficient. With the gradual improvement of carbon emission levels of the manufacturing industry, the impact of economic growth, foreign direct investment and energy intensity on the carbon emission of the manufacturing industry is gradually increasing. In addition, China's manufacturing industry has a huge space for emission reduction. Because with the gradual improvement of the carbon emission level of the manufacturing industry, economic growth, foreign direct investment and energy intensity increase promote an increase in carbon emissions in the manufacturing industry (especially the sum of coefficients of the 70th, 80th, 90th and 95th percentiles are greater than 1). Therefore, we should adequately deal with the relationship between economic growth and carbon emissions, pay attention to the changes in total carbon emissions while focusing on foreign direct investment and energy intensity improvement, especially making good use of the larger emission reduction space in high emission areas, and reduce the total emissions of China's manufacturing industry through a reasonable combination of economic growth, foreign direct investment and energy intensity.

The empirical results of the control variables included in the model also provide reference information. First, we can observe the impact of urbanization rate on carbon emissions. At the low quantiles (20th and 30th), the coefficient of urbanization rate is significant; at other quantiles, it is not significant. All coefficients of *URB* are positive, which means that higher urbanization rate will lead to higher carbon emissions of the manufacturing industry. In comparison, the impact of urbanization in low emission areas on manufacturing carbon emissions is greater than that in high emission areas, because its coefficient elasticity is greater. The reason may be that the increase in urbanization rate not only causes the increase of urban population, but also leads to the rise in demand for high emission products such as vehicles and real estate, and then causes the increase of carbon emissions in the manufacturing industry. Second, the coefficient of dependence on foreign trade is not significant in all quantiles. All coefficients are positive, but the elasticity is very weak; that is, the dependence on foreign trade will have a positive impact on the carbon emissions of China's manufacturing industry, which shows that China's manufacturing industry has a weak carbon leakage phenomenon. Third, the impact of total population on carbon emissions; we can see that the impact of total population on carbon emissions is obvious heterogeneity. At the 5th, 20th, 30th and 40th quantiles, the *POP* coefficient was positive, but not significant at the 10% level. In the 50th, 60th, 70th, 80th, 90th and 95th quantiles, the *POP* coefficient was negative, but not significant at the level of 10%. In low emission areas, population size has a positive impact on carbon emissions of manufacturing industry, while in high emission areas, population size hurts carbon emissions of manufacturing industry. This shows that population size is not an important factor affecting carbon emissions of the manufacturing industry in these regions. In addition, in the low quantile (5th and 20th quantiles), the energy structure coefficient is not significant, but the high quantile (30th and 40th quantiles), the 50th, 60th, 70th, and 80th quantiles, are at the level of 5%, whereas at the 90th and 95th quantiles they are significant at the level of 1%; the energy structure coefficient is significant. All these results above proved that it is necessary to further optimize the energy structure for low emission areas.

5. Conclusions and Policy Recommendations

Based on panel data of 30 provinces in China from 2000 to 2013, this paper studied the impact of FDI, economic growth and energy intensity on carbon emissions of China's manufacturing industry by a two-way fixed-effect panel quantile regression model. The results show that the impact of economic

growth, foreign direct investment and energy intensity on the carbon emissions of the manufacturing industry is different under different levels of carbon emissions from the manufacturing industry and different regions, with obvious heterogeneity, and economic growth plays a decisive role in the carbon emissions of the manufacturing industry. Among them, economic growth has a positive impact on the carbon emissions of the manufacturing industry, and the higher the impact of economic growth of high emission provinces on the carbon emissions of the manufacturing industry is, the more significant the impact of foreign direct investment on the carbon emissions of the manufacturing industry is regional heterogeneity, and the impact is more significant in high emission provinces and supports the hypothesis that there is a pollution paradise in China's manufacturing industry, but there is no halo effect hypothesis. The reduction of energy intensity also does not have a positive effect on the reduction of carbon emissions. The high impact of energy intensity in high emission provinces on the carbon emissions of their manufacturing industries, indicates that there is energy rebound effect in China's manufacturing industry. Finally, it is confirmed that China's manufacturing industry has a vast space for emission reduction.

According to the above research results, in order to reduce the total carbon emissions of China's manufacturing industry and improve China's environmental quality, the following three policies are recommended.

- (1). Based on the hypothesis of pollution heaven and halo effect in different provinces, China should try to assess the impact of foreign direct investment on the environment before the introduction of foreign capital into China's manufacturing industry. Especially in high emission areas, the level of FDI should be improved. Moreover, through financial, tax and industrial policies to limit the inflow of high emission foreign capital, encourage the entry of high-tech and advanced management experience.
- (2). The Chinese government should not only consider the energy conservation brought about by technological change but also pay attention to the energy rebound effect, to avoid overestimating the energy conservation brought about by the technological progress of the industry.
- (3). China should adopt different carbon emission policies in regions with different carbon emission levels and properly handle the relationship between economic growth and carbon emissions. Based on the different characteristics of economic growth in each province, targeted measures are taken to reduce the CO₂ emission of the manufacturing industry. There is a huge space for China's manufacturing industry to reduce emissions, and we should encourage manufacturing enterprises to join the carbon trading market.

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