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The Relationship between CO_2 Emissions, Air Pollution, and Tourism Flows in China: A Panel Data Analysis of Chinese Provinces

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Abstract: This study quantitatively investigated the relationship between climate change (proxied by CO_2 emissions), air pollution (proxied by PM2.5 concentration levels and PM10 and SO_2 emissions), and tourism flows (proxied by inbound and domestic tourist arrivals) using panel data for 30 Chinese provinces from 2010 to 2017. The results demonstrate a long-term equilibrium relationship between CO_2 emissions, air pollution variables, and tourism flows (including the number of inbound and domestic tourists). The panel data model results show that CO_2 emissions have an opposite effect on inbound and domestic tourist arrivals, while domestic and inbound tourists positively affect CO_2 emissions. PM2.5 level and PM10 and SO_2 emissions all have a negative effect on the number of tourists. There is bidirectional causality between CO_2 emissions and domestic tourist arrivals, which means CO_2 emissions and domestic tourist arrivals have a two-way effect. A one-way causality running from PM2.5 to inbound tourist arrivals and SO_2 emissions to domestic tourist arrivals was found. Moreover, we also found bidirectional causality between PM10 and inbound tourist arrivals and PM10 and domestic tourist arrivals. Variance decomposition function results suggest that PM10 and SO_2 emissions have stronger effects on inbound tourist arrivals in the long term, while CO_2 emissions and PM10 have stronger power in explaining innovations in domestic tourist arrivals. The movements in the domestic tourist arrivals do significantly affect CO_2 emissions in the long run. The study provides theoretical implications and guidance for achieving a healthy and sustainable tourism industry.

Keywords: CO_2 emissions; PM2.5 concentration; tourist activity; China

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Citation: Zikirya, B.; Wang, J.; Zhou, C. The Relationship between CO_2 Emissions, Air Pollution, and Tourism Flows in China: A Panel Data Analysis of Chinese Provinces. *Sustainability* **2021**, *13*, 11408. https://doi.org/10.3390/su132011408

Academic Editor: Mohammad Aslam Khan Khalil

Received: 30 July 2021
Accepted: 12 October 2021
Published: 15 October 2021

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1. Introduction

Global tourism has witnessed significant growth over the past decades, especially in China. According to the China Statistical Yearbook published by China's National Bureau of Statistics, since the 1980s, China's tourism industry has experienced tremendous growth, with inbound tourists increasing from 1.81 million in 1978 to 139.78 million in 2017, making China one of the world's largest host countries for inbound tourism [1]. Tourism has become one of the strongest and largest industries internationally and is regarded as an engine of economic development [2,3]. A growing body of literature has explored various factors that influence the attraction of tourists, such as extreme weather events [4], tourist security [5,6], and government policies [2].

Global warming and air pollution pose a risk to the environment and human health, and they are the most important environmental issues currently facing societies. As tourism is often considered a highly environmentally sensitive economic sector [7], it is particularly important to consider the challenge that global warming and air pollution pose to growth in the sector, and not least its impact on tourism attractiveness. On the one hand, studies

have shown that tourism is severely impacted by climate change and that this will be long-lasting [8]. The United Nations World Tourism Organization considers the range of hazards caused by climate change, such as global warming, to be the most serious challenge to sustainable tourism. A number of scholars argue that the impact of global warming on developing countries where tourism is the mainstay must be completely accounted for in the formulation of relevant policies, international negotiations, and international development assistance [9,10]. Meanwhile, air pollution is a danger to human health, and the environment has become an increasing global concern [11]. Air pollution has posed a threat to the environment, atmospheric visibility, and especially human health in many countries and regions of the world [12]. The World Health Organization (WHO) reported that 4.2 million deaths were associated with outdoor air pollution worldwide in 2016, and about 7 million deaths worldwide each year are attributed to air pollution [13]. Air quality issues have become a major challenge for sustainable tourism development [14]. Poor air quality endangers public health, causes dense fog, and obscures the views offered by tourist attractions, thereby reducing visitors' willingness to travel [15].

Given the growing concern for global warming mainly caused by CO_2 emissions and air quality over recent decades, scholars have begun to address the association between CO_2 emissions, air pollution, and tourism. Tourism and CO_2 emissions can be considered mutually influencing [16], and some scholars have examined the effects of tourism on CO_2 emissions [17–19]. Several works have dealt with the influence of CO_2 emissions on tourism [20–22]. The impact of CO_2 emissions on tourism in different regions may be different. Tourism is highly dependent on the climatic conditions of a particular destination, and global warming caused by CO_2 emissions will lead to changes in the climatic comfort of tourism, which will affect long-term tourism flows [23,24], and further temperature increases in low-latitude regions will affect their climatic comfort and lead to a decrease in their tourist arrivals. Coastal regions will suffer from sea-level rise, typhoons, hurricanes, tsunamis, and other disasters, which will reduce their tourist flows. Since there are some good sides to every bad situation, a warmer climate may lead to a greater flow of tourists to higher latitudes, thus increasing the number of visitors to these regions and increasing their length of stay. There is also literature that explores the impact of CO_2 emissions reduction policies on tourism flows [23,24].

Several studies have identified the negative effects of air pollution on tourism development [25,26]. For example, using data from 190 countries, Hemmati et al. (2020) investigated the relationship between the number of international visitors and concentrations of PM2.5 and found a significant relationship in rural areas. As air pollution in a country's rural areas increases, the number of international tourists visiting the country has decreased [2]. Through panel data on 30 Chinese provinces for the period 2001 to 2013, the results of Deng et al. (2017) suggest that air pollution has a significant inhibitory influence on the numbers of international visitors to China [27]. Several studies have found that air quality plays a critical role in tourist decisions, thereby affecting tourism [28]. For example, by surveying 600 U.S. and Australian residents, Becken et al. (2017) found that a negative impression of China's air quality led to an extremely low willingness to visit this country [29]. In addition, some studies have conversely examined the impact of tourism development on air quality. They found that air pollution is an external core cost of tourism and that the contribution of tourist behavior to air pollution cannot be ignored [30,31].

In summary, despite growing recognition of the tourist industry's vulnerability to CO_2 emission and air pollution, the relationship between global warming, air pollution, and tourism remains uncertain. Specifically, although the WTO recognized the bidirectional relationship between CO_2 emissions and tourism [32], the existing literature has mostly studied the impact of tourism on CO_2 emissions, ignoring the impact of CO_2 emissions on tourism. In addition, existing studies on the effects of air pollution on tourism have focused on the effects of air pollution on destination image [29], tourism experience, and intention to visit [33] through questionnaires administered to tourists or potential tourists. However, research has neglected inquiry into the impact of air pollution on tourism flows, and

previous studies have mainly examined PM2.5 as a proxy for air pollutants and the effects of other major air pollutants (e.g., PM10, SO_2 emissions) have rarely been explored. Given that each of these air pollutants may pose a health risk to travelers and undermine the attractiveness of the destination to potential tourists [34,35], there is a need to understand how and to what extent major air pollutants affect tourism flows.

The purpose of this study was to attend to the above gap in the study field, and the contribution of this study mainly includes the following aspects. First, we empirically quantified the bidirectional relationship between CO_2 emission and tourism flows, rather than the unidirectional effect of tourism on CO_2 emission that has been studied in most of the previous literature. Second, little attention has been paid in the existing literature to the effects of air pollutants other than PM2.5 concentrations on tourism; thus, we studied the effects of three major air pollutants (PM2.5, PM10, and SO_2) on domestic and inbound tourist arrivals. Third, because domestic and inbound tourists differ in number and demographic characteristics, these differences affect their destination choice and travel behavior, which may influence their relationship with CO_2 emissions and air pollution. Therefore, in exploring tourism flows in relation to CO_2 emissions and air pollution, we have divided tourism flows into domestic and inbound tourist arrivals. Lastly, the results of our empirical study may help policymakers to develop appropriate environmentally friendly tourism strategies. In this study, panel data for 30 Chinese provinces from 2010 to 2017 were used. Since the main cause of global warming is CO_2 emissions caused by human activities [36], global warming is represented by CO_2 emissions in this study. PM2.5 concentration levels and PM10 and SO_2 emissions were selected to represent air pollution.

2. Data and Methodology

2.1. Data and Data Sources

Annual data for thirty Chinese provinces (excluding Tibet, Taiwan, Hong Kong, and Macau) from 2010 to 2017 were used in this study to address the relationship between CO_2 emissions, tourist arrivals, and air pollution. Tourism flows are represented by two variables, namely inbound tourist arrivals (ITA) and domestic tourist arrivals (DTA), both of which are derived from the China Tourism Statistical Yearbooks (2011–2018). Data on CO_2 emissions for each province were collected from the China Emission Accounts and Datasets (CEADs) [37,38]. Air pollution was represented by PM2.5 concentration and PM10 and SO_2 emissions. PM2.5 concentration data for 2010–2017 were obtained from satellite remote sensing and ground monitoring with a spatial resolution of 1×1 km. Data of PM2.5 concentration levels were estimated by combining aerosol optical depth (AOD) data obtained from MISR, NASA Moderate Resolution Imagine Spectroradiometer (MODIS), and SeaWiFS instruments with GEOS-Chem chemical transport models, followed by calibration of regional ground observations of the total and component masses applying geographically weighted regression (GWR). High-resolution data on PM2.5 are free public data provided by the Atmospheric Composition Analysis Group at Dalhousie University [39,40]. PM10 and SO_2 emissions data were collected from the Multi-resolution Emission Inventory for China (MEIC, http://meicmodel.org, accessed on 13 May 2021) [41,42]

The statistical descriptions of the selected variables are displayed in Table 1. Figure 1 provides a scatter plot and a distribution overlay for numbers of inbound and domestic tourist arrivals; CO_2, PM2.5, PM10, and SO_2 emissions data are displayed as box plots. As seen in Figure 2, the number of inbound arrivals maintained steady growth during the study period (a 20.88% increase from 2010 to 2017), while the number of domestic tourists increased significantly (a 58.65% increase from 2010 to 2017). CO_2 emissions increased from 9134 Mt in 2010 to 11303 Mt in 2017. PM2.5 concentration levels first decreased, then increased, and finally showed a decreasing trend. Both SO_2 emissions and PM10 continued to decline during the study period.

Table 1. Statistical depiction of the variables for all the 30 Chinese provinces during the period 2010 to 2017.

	Unit	Mean	Median	Max	Min	Std.Dev
ITA	10^4 person	234.39	109.28	3507.21	0.30	472.01
DTA	10^4 person	686.98	359.55	4247.27	8.84	842.85
CO_2 emissions	Mt	251.91	182.31	1552.01	0.81	225.04
PM2.5	$\mu g/m^3$	412.10	282.11	1177.97	19.61	274.46
PM10	Million ton	46.89	44.10	151.30	4.56	30.89
SO_2 emissions	Million ton	71.68	52.96	299.71	2.68	58.27

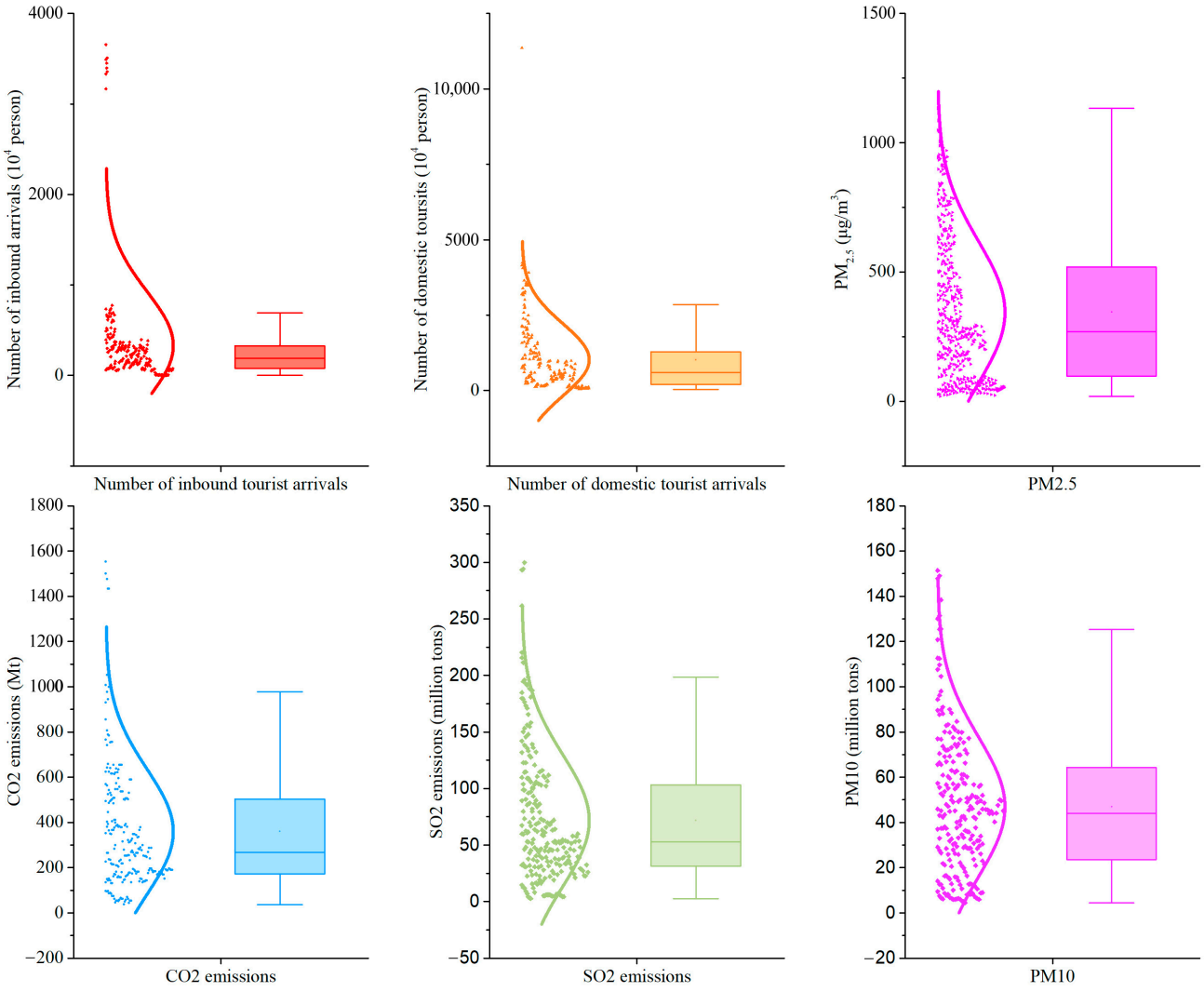


Figure 1. Box plot of the number of inbound and domestic tourist arrivals; data of CO_2 emissions, SO_2 emissions, and PM2.5 and PM10 with scatter plot and distribution overlay.

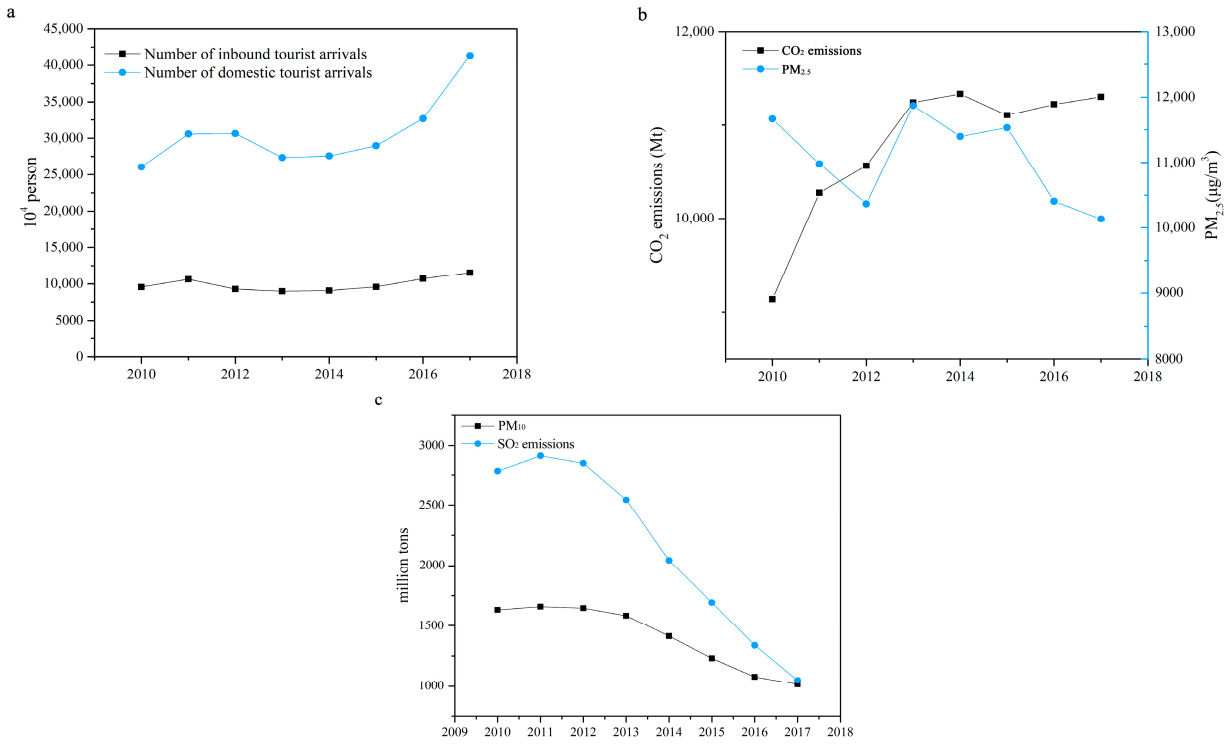


Figure 2. Temporal change of selected variables from 2010 to 2017. (**a**) Changes in the number of inbound tourist arrivals and domestic tourist arrivals; (**b**) changes in the CO_2 emissions and PM2.5; (**c**) changes in the PM10 and SO_2 emissions.

2.2. Panel Data Model

Before conducting a series of tests, we treated the data as natural logarithms to ensure that the estimated coefficients in models could be explained as elasticity coefficients, and we removed the effect of heteroskedasticity in the time-series data [43,44]. The following panel data models were employed in this study for the purpose of exploring the relationship between CO_2 emissions, air pollution, and tourist arrivals:

$$InITA_{it} = \alpha + \beta_1 InCE_{it} + \beta_2 InPM_{2.5it} + \beta_3 InPM_{10it} + \beta_4 InSE_{it} + \varepsilon_{it} \quad (1)$$

$$InDTA_{it} = \alpha + \beta_5 InCE_{it} + \beta_6 InPM_{2.5it} + \beta_7 InPM_{10it} + \beta_8 InSE_{it} + \varepsilon_{it} \quad (2)$$

where *ITA* represents the number of inbound arrivals; *DTA* stands for the number of domestic tourists; *CE* represents CO_2 emissions; SE stands for SO_2 emissions; α stands for the intercept term; β_i is the undetermined coefficients; *i* denotes the provinces; and *t* stands for time.

The analysis in this study was carried out on the basis of a sequence of estimation procedures consisting of five main steps. First, the stationarity of the four variables was identified using the panel unit root test, in this case, the ADF–Fisher and Levin–Lin–Chu (LLC) tests. Second, we employed the Pedroni cointegration test to examine the existence of cointegration between the research variables. Third, the long-term relationship between research variables was explored through the panel data model. Fourth, variance decomposition and impulse response methods were employed to reveal the proportion of one selected variable explaining the changes in the other variable, and we observed the effect of a change in one variable by itself and in other variables. Finally, the bidirectional causality relationship between variables was investigated using the Granger causality method, which was on the basis of the vector error correction model (VECM).

2.2.1. Panel Unit Root Tests

The majority of time-series data are not stationary, and random trends in variables may produce misleading results and spurious regressions if regression analysis is performed

directly [45]. Therefore, prior to establishing a panel data model, it was necessary to use unit root tests. Compared with the unit root test based on cross-sectional series and time-series data, the panel unit root test is more advantageous and widely used for testing unit roots in panel data. Two different models of panel unit root tests were employed in this study, i.e., the LLC tests and the ADF–Fisher tests. The LLC tests are aimed at examining the common unit root and can be expressed as follows:

$$\Delta y_{it} = Øy_{i,t-1} + z'_{it}\gamma_{it} + \sum_{j=1}^{p} \theta_{ij}\Delta y_{i,t-1} + \mu_{it} \quad (3)$$

where z'_{it} is the column vector of exogenous variables; γ_{it} represents the regression parameters vectors; μ_{it} stands for the white noise; and Ø represents the autoregressive coefficient. If Ø = 0, the test does not reject the null hypothesis, and there is a unit root. If Ø < 0, the test rejects the null hypothesis and Δy_{it} is considered to be stationary (including trend-stationary).

The individual unit root can be examined by the ADF–Fisher tests. When π_i is given in the form of *p*-values, any individual cross-sectional unit root test will be I. Afterward, with the null hypothesis for a unit root of all N cross-sections, the following equation can be obtained [46]:

$$\mathrm{I} = -2\sum_{i=1}^{n} \log(\pi_i) \rightarrow x^2_{2N} \quad (4)$$

ADF–Choi demonstrated that

$$\mathrm{Z} = \frac{1}{\sqrt{N}_{i=1}} \sum_{i=1}^{N} \varphi^{-1}(\pi_i) \rightarrow N(0,1) \quad (5)$$

where φ^{-1} denotes the inverse of the standard normal cumulative distribution function. The null hypothesis of the ADF–Fisher test can be written as follows:

$$H_0 : \alpha_i = 0, \text{ for all i} \quad (6)$$

The alternative hypothesis is as below:

$$H_1 : \begin{cases} \alpha_i = 0, \ for\ i = 1, 2, \ldots\ldots N_i \\ \alpha_i < 0\ for\ i = N+1, N+2, \ldots, N \end{cases} \quad (7)$$

2.2.2. Panel Cointegration Tests

The next step after completing the unit root test was the cointegration test. The regression of single integer variables without a cointegration relationship is still a spurious regression. In this study, a panel cointegration test examined the existence of a long-term relationship between CO_2 emissions, air pollution variables, and the numbers of domestic tourist arrivals and inbound tourist arrivals. The panel cointegration tests used here were the Kao tests. The cointegration tests require all the research variables to be integrated in the same order. In its general form, the cointegration test can be specified as follows:

$$y_{it} = \alpha_i + \delta_i t + \beta_{1i}x_{1it} + \beta_{2i}x_{2it} + \ldots + \beta_{mi}x_{mit} + \varepsilon_{it} \quad (8)$$

where *t* stands for the number of observations over a period of time; *i* denotes the number of individual cells in the model; *m* represents the number of regression variables; β_{1i}, β_{2i}, ..., β_{mi} are the slope coefficients; α_i is the specific intercept; and x_{it} and y_{it} are assumed to be first-order integrals.

2.2.3. Panel Granger Causality Test

When the model is cointegrated, the Granger causality tests, on the basis of VECM, can be applied to further measure the interaction between CO_2, air pollution, and tourist

arrivals. Granger causality is a classic and widely used econometric method to explore whether the past values of one variable affect predicting future values of another variable. The basic principle of Granger causality is that assuming there are two variables X and Y, X is the Granger-cause of Y when the use of past values of X improves the forecast of the present values of Y. The Granger causality model was applied using the VECM models as below:

$$\Delta y_{it} = \alpha_{it} + \beta_{it} ect_{it-1} + \sum_{i=1}^{m} \delta_{it} \Delta x_{it-1} + \sum_{i=1}^{m} \vartheta_{it} \Delta y_{it-1} + \mu_{it} \quad (9)$$

$$\Delta x_{it} = \alpha_{it} + \beta_{it} ect_{it-1} + \sum_{i=1}^{m} \delta_{it} \Delta y_{it-1} + \sum_{i=1}^{m} \vartheta_{it} \Delta x_{it-1} + \mu_{it} \quad (10)$$

where Δ denotes the first difference operator; α_{it} represents the constant term; β_{it}, δ_{it}, and ϑ_{it} denote the parameters; and ect_{it-1} stands for the lagged error correction term gained from the cointegration equations.

2.2.4. Impulse Response Analysis

The impulse response function was applied to quantify the long-term effect of the explanatory variables on the explained variables. The impulse response function is a classical econometric analysis tool provided by the VEC modeling system. It affects the trajectory of the current and future values of the endogenous variables through the standard deviation of the random disturbance term, which accurately characterizes the dynamics and interactions between the variables. The basic form of vector auto-regression (VAR) model is given by the following [47]:

$$x_t = a_1 x_{t-1} + a_2 x_{t-2} + b_1 y_{t-1} + b_2 y_{t-2} + \varepsilon_{1t} \quad (11)$$

$$y_t = c_1 x_{t-1} + c_2 x_{t-2} + d_1 y_{t-1} + d_2 y_{t-2} + \varepsilon_{2t} \quad (12)$$

where $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ represents the disturbing term and the need to meet the following characteristics:

$$\begin{cases} E(\varepsilon_t) = 0, \forall_t \\ var(\varepsilon_t) = E(\varepsilon_t \varepsilon_t') \\ E(\varepsilon_t \varepsilon_t') = 0, \forall_t \neq s \end{cases} = \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{pmatrix}, \forall_t \quad (13)$$

2.2.5. Variance Decomposition Function

Variance decomposition function is employed to show the response of each structural shock to the variation in the variables, and it assesses the relative amount of information contributed by the variable relative to other variables. Variance decomposition analysis is a test of causality outside the study sample period on the one hand and a test of the relative importance of every random disturbance term influencing the variables in the VAR on the other. The basic form of variance decomposition analysis is as follows:

$$y_{it} = \sum_{j=1}^{k} (c_{ij}^{(0)} e_{jt} + c_{ij}^{(1)} e_{jt} + c_{ij}^{(2)} e_{jt} + \ldots) \quad (14)$$

The right-hand of the equation represents the total influence of the j_{th} disturbing term εj on the yi.

3. Empirical Results and Discussion

3.1. Panel Unit Root Test Result

Prior to conducting a long-term relationship test between study variables, the unit root test was necessary to verify the stationarity of the variables to prevent spurious regressions. In this paper, ADF–Fisher and LLC panel unit root tests were adopted to test the stationary of all research variables and their integration order, and the result is given in Table 2. All variables except domestic tourists were stationary after first differencing with significance

levels below 5%. This finding indicates that all variables rejected the null hypothesis (assuming that variables had unit roots) and were stationary at the first difference.

Table 2. Results of panel unit root test.

	Level	First Difference
Levin–Lin–Chu (comment root)		
ITA	−12.9095 ***	−71.9882 ***
DTA	−4.0668 ***	−16.8351 ***
CO_2	−3.6751 ***	−12.7641 ***
PM2.5	0.70218	−15.3544 ***
PM10	−4.74984 ***	−111.218 ***
SO_2	6.3292	−31.5600 ***
ADF–Fisher (individual root)		
ITA	93.6139 ***	158.855 ***
DTA	68.5796	116.167 ***
CO_2	65.6518	114.992 ***
PM2.5	23.4373	122.220 ***
PM10	43.8621	83.5461 **
SO_2	15.9819	123.844 ***

Note: *** represents significance at the 1% level; ** denotes significance at the 5% level.

3.2. Panel Cointegration Test Results

Since the panel unit root test showed that all study variables were first-order difference stationary, we applied the panel Kao cointegration tests to verify whether there was a cointegration relationship between CO_2 emissions, air pollution, and tourist arrivals in China from 2010 to 2017. The panel Kao cointegration test results for panels A and B are given in detail in Table 3.

Table 3. Kao residual cointegration test results for panel A and panel B.

	Panel A (Inbound Tourist Arrivals, CO_2 Emissions, SO_2 Emissions, PM2.5 and PM10)	Panel B (Domestic Tourist Arrivals, CO_2 Emissions, SO_2 Emissions, PM2.5 and PM10)
t-Statistic	−2.228023	−2.413700
Prob.	0.0129	0.0079

As shown in Table 3, panel A rejected the nullity of non-cointegration at the significance level of 5%, revealing a long-term equilibrium relationship between CO_2 emissions, air pollution, and inbound tourist arrivals. Panel B rejected the nullity of non-cointegration at the significance level of 1%, meaning a long-term equilibrium relationship between CO_2 emissions, air pollution, and domestic tourist arrivals.

3.3. Panel Data Model Results

Given the results showing a long-term equilibrium relationship between CO_2 emissions, air pollution, and tourist arrivals, we used the panel data model to investigate the variables' positive or negative long-term relationship.

It can be seen from Table 4 that when other factors were held constant, a 1% increase in CO_2 emissions was associated with a 0.17% decrease in inbound tourists and a 0.41% increase in domestic tourists. This indicates that an increase in CO_2 emissions has a negative effect on inbound tourists and a positive effect on domestic tourists. The negative effect of CO_2 emissions on inbound tourists may be due to the fact that the destinations of inbound tourists are mainly concentrated in the eastern regions of Beijing, Shandong, and the southeastern coastal region (according to the China Statistical Yearbook, the proportion of inbound tourists from these regions reached 65% of the total number of inbound tourists

in 2017). According to previous studies, global warming and climate change can have serious consequences for tourism in coastal areas [48,49]. The increase in CO_2 emissions will reduce the comfort level of tourism by increasing the temperature in these already warm regions. In addition, higher temperatures due to increased CO_2 can cause sea-level rises and extreme weather events in these coastal regions, which can also make travel less attractive; the positive effect of CO_2 on domestic tourists may be due to the fact that warmer temperatures make western and high-latitude regions more attractive, thus increasing domestic tourists.

Table 4. The impact of CO_2 emissions and air pollution on tourist arrivals.

Explanatory Variables	CO_2 Emissions	PM2.5 Concentration	PM10 Emissions	SO_2 Emissions
ITA as independent variable	−0.1722 (−1.36)	−0.4147 (−2.99) ***	−0.0320 (−0.13)	−0.0344 (−0.26)
DTA as independent variable	0.4068 (2.94) ***	−0.0997 (−0.66)	−0.2665 (0.99)	−0.3258 (−2.28) **

Note: *** represents significance at the 1% level; ** denotes significance at the 5% level.

A 1% increase in PM2.5 levels decreased inbound and domestic visitors by 0.41% and 0.10%. The influence of PM2.5 levels was more pronounced for inbound tourist arrivals than for domestic tourist arrivals, which indicates that international tourists are more sensitive to PM2.5 concentration than domestic tourists. A 1% increase in PM10 decreased inbound and domestic visitors by 0.03% and 0.27%, respectively. Moreover, a 1% increase in SO_2 emissions decreased the number of inbound and domestic visitors by 0.03% and 0.32%, respectively, indicating that SO_2 emissions greatly influence domestic arrivals.

Given the bidirectional impact between climate change and tourism [32], we also verified the impact of inbound and domestic tourist arrivals on CO_2 emissions (Table 5). The results show that tourist arrivals positively influenced CO_2 emissions, a finding consistent with related studies [18,50,51]. It is worth noting that domestic tourist arrivals have a greater significant influence on CO_2 emissions than inbound tourist arrivals in China. The possible reasons for this are as follows: on the one hand, the number of domestic tourists in China is significantly higher than inbound tourists. On the other hand, an increasing number of domestic tourists are choosing to travel by car [52,53], which can cause an increase in CO_2 emissions.

Table 5. The impact of tourist arrivals on CO_2 emissions.

Explanatory Variables	ITA	DTA
CO_2 emissions as independent variable	0.0488 (−1.31)	0.0978 (2.91) ***

Note: *** represents significance at the 1% level.

3.4. Panel Granger Causality Test Result

The results from Table 3 show the presence of a long-term equilibrium relationship between CO_2 emissions, PM2.5 levels, PM10 and SO_2 emissions, and tourism flows (both inbound and domestic tourist arrivals). Therefore, a Granger causality model can be performed. This method provides a practical analytical tool for determining causal relationships between variables from a statistical perspective. Table 6 shows the causal relationship between CO_2 emissions, air pollution variables, inbound tourist arrivals, and domestic tourist arrivals.

Table 6. Panel Granger causality tests results.

Null Hypothesis	F-Statistic	Prob.
CO_2 emissions and tourist arrivals		
CO_2 emissions do not Granger-cause ITA	0.52773	0.59
ITA does not Granger-cause CO_2 emissions	2.78323	0.06 *
CO_2 emissions do not Granger-cause DTA	4.91441	0.01 ***
DTA does not Granger-cause CO_2 emissions	4.07234	0.02 **
Air pollution and tourist arrivals		
PM2.5 does not Granger-cause ITA	2.33061	0.10 *
ITA does not Granger-cause PM2.5	1.15958	0.31
PM2.5 do not Granger-cause DTA	1.66343	0.19
DTA does not Granger-cause PM2.5	1.73113	0.18
PM10 does not Granger -cause ITA	3.55809	0.03 **
ITA does not Granger-cause PM10	3.81945	0.02 **
PM10 does not Granger-cause DTA	7.32108	0.00 ***
DTA does not Granger-cause PM10	13.4514	0.00 ***
SO_2 emissions do not Granger-cause ITA	0.91890	0.40
ITA does not Granger-cause SO_2 emissions	1.73397	0.18
SO_2 emissions do not Granger-cause DTA	4.07635	0.02 **
DTA does not Granger-cause SO_2 emissions	0.73649	0.48
CO_2 emissions and air pollution		
CO_2 emissions do not Granger-cause PM2.5	1.60589	0.20
PM2.5 does not Granger-cause CO_2 emissions	1.13524	0.32
CO_2 emissions do not Granger-cause PM10	0.60357	0.54
PM10 does not Granger-cause CO_2 emissions	0.97923	0.37
CO_2 emissions do not Granger-cause SO_2 emissions	0.39033	0.67
SO_2 emissions does not Granger-cause CO_2 emissions	0.39373	0.67

Note: * stands for significance at the 10% level; ** denotes significance at the 5% level; *** represents significance at the 1% level.

There was a unidirectional causal relationship from inbound tourist arrivals to CO_2 emissions, implying that inbound tourist arrivals directly affect CO_2 emissions. We also found bidirectional causality between CO_2 emissions and domestic tourist arrivals, which means that CO_2 emissions and the number of domestic tourists have a two-way effect. Climate change affects the inflow of domestic tourists, and, in turn, domestic tourist arrivals affect CO_2 emissions; a one-way causality running from PM2.5 to inbound tourist arrivals was also found. Moreover, we found bidirectional causality between PM10 and inbound tourist arrivals and PM10 and domestic tourist arrivals. There was also a unidirectional causal relationship from SO_2 emissions to domestic tourist arrivals, implying that SO_2 emissions directly affect domestic tourist arrivals. In addition, no causal relationship was found in the CO_2 emission and air pollution variables.

3.5. Impulse Response and Variance Decomposition Analysis

The impulse response function analyzes how variables are destabilized by shocks generated by other variables. In particular, impulse response analysis depicts the path of the effect of a random disturbance term on a shock of one standard deviation to an endogenous variable. Impulse response analysis was used to understand the extent to which fluctuations in one variable affect the other variable, and the results are presented in Figure 3. A shock of one standard deviation to CO_2 emissions led to the biggest change in inbound tourist arrivals and domestic tourist arrivals in the second and third period, respectively, implying that CO_2 emissions shocks have a lagged effect on inbound and domestic tourist arrivals. The response of domestic tourist arrivals to a shock of one standard deviation to CO_2 emissions, PM2.5 levels, and PM10 and SO_2 emissions was greater than the response of inbound tourist arrivals.

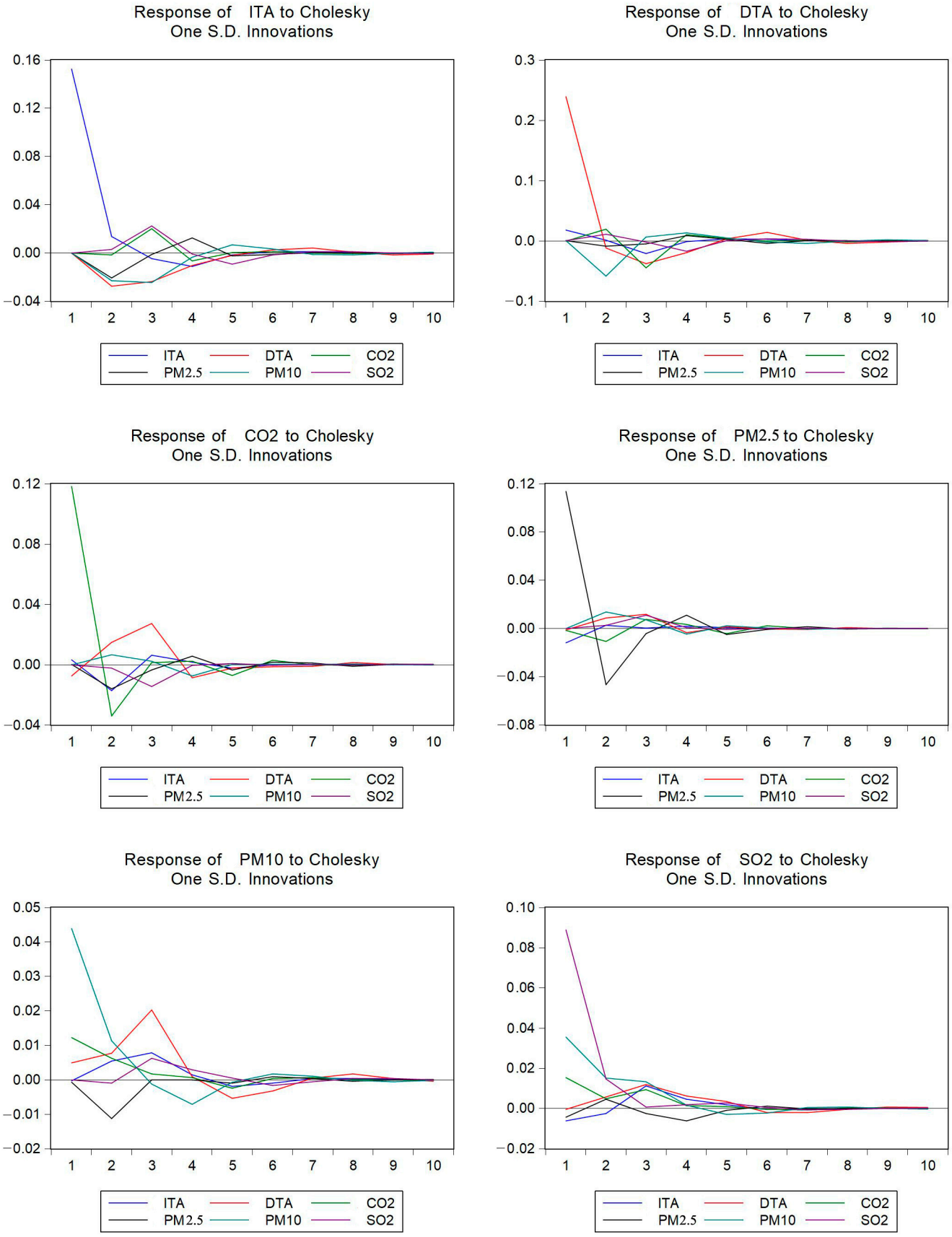


Figure 3. Impulse response graphs.

The variance decomposition function was applied to evaluate the influence magnitude on the basis of the impulse response results. It can be seen from Table 7 that at the five-year forecasting horizon, PM10, SO_2, and PM2.5 and CO_2 emissions explain 6.40%, 2.37%, 2.07%, and 1.42% of inbound arrivals, respectively, with 87.74% of inbound arrivals being explained by their shocks. In the ten-year forecast horizon, the contributions of PM10, SO_2, PM2.5, and CO_2 emissions are equivalent to 6.44%, 2.39%, 2.08%, and 1.42%, respectively. In the case of domestic tourist arrivals, at the ten-year forecasting horizon, PM10, CO_2 emissions, SO_2, and PM2.5 explain 5.93%, 3.99%, 0.66%, and 0.21% of domestic tourist arrivals, respectively. These results suggest that PM10 and SO_2 emissions have stronger effects on inbound tourist arrivals in the long term, while CO_2 emissions and PM10 have stronger power in explaining innovations in domestic tourist arrivals. From Table 8, ITA, DTA, PM2.5, and PM10 and SO_2 emissions explain 1.82%, 5.76%, 1.81%, 0.60%, and 1.22% of CO_2 emissions, respectively, with 88.80% of CO_2 emissions being explained by their shocks. We can conclude that movements in domestic tourist arrivals do significantly affect CO_2 emissions in the long run.

Table 7. Variance decomposition results of tourist arrivals.

Variance Decomposition of Inbound Tourist Arrivals						
Period	**S.E.**	**ITA**	**CO_2**	**PM2.5**	**PM10**	**SO_2**
1	0.153529	100	0	0	0	0
2	0.158643	94.98636	0.070788	1.702694	3.171924	0.068238
3	0.163959	88.97187	1.126333	1.64264	6.252844	2.006316
4	0.165176	88.22306	1.430034	2.072872	6.28193	1.992105
5	0.165665	87.73703	1.421805	2.074043	6.395377	2.371741
6	0.165725	87.67342	1.422913	2.078009	6.436289	2.389364
7	0.165732	87.66927	1.423662	2.077885	6.437616	2.391571
8	0.165738	87.66414	1.424128	2.07812	6.44022	2.393391
9	0.165738	87.66386	1.424133	2.07813	6.440403	2.39347
10	0.165738	87.66382	1.42416	2.078128	6.440423	2.393473
Variance Decomposition of Domestic Tourist Arrivals						
Period	**S.E.**	**DTA**	**CO_2**	**PM2.5**	**PM10**	**SO_2**
1	0.238413	100	0	0	0	0
2	0.247748	92.82843	0.897757	0.097324	5.954872	0.221615
3	0.254735	90.06818	3.893509	0.12924	5.698757	0.210316
4	0.256957	89.316	3.930198	0.20388	5.918364	0.63156
5	0.25708	89.23469	4.002903	0.204506	5.921477	0.636424
6	0.257547	89.23234	3.989722	0.206273	5.911941	0.65972
7	0.25758	89.21039	3.98926	0.207581	5.931987	0.660783
8	0.257627	89.20652	3.994201	0.207686	5.930346	0.661243
9	0.257638	89.20155	3.993831	0.207672	5.934044	0.662902
10	0.257641	89.20062	3.994833	0.207695	5.933953	0.662903

Table 8. Variance decomposition results of CO_2 emissions.

Period	**S.E.**	**CO_2**	**ITA**	**DTA**	**PM2.5**	**PM10**	**SO_2**
1	0.118641	100	0	0	0	0	0
2	0.12675	95.46557	1.665048	0.998143	1.57984	0.259359	0.032041
3	0.130695	89.79003	1.799593	5.345821	1.553795	0.274213	1.236544
4	0.131351	88.93956	1.797914	5.719169	1.720677	0.597185	1.225492
5	0.13164	88.84902	1.817395	5.735163	1.780359	0.594792	1.223269
6	0.131695	88.8294	1.816422	5.74015	1.795808	0.594356	1.223861
7	0.131702	88.81886	1.816565	5.745635	1.800581	0.594623	1.223735
8	0.131715	88.80317	1.816338	5.755086	1.805469	0.596314	1.223624
9	0.131717	88.80206	1.816448	5.755253	1.805651	0.596822	1.223763
10	0.131717	88.80181	1.816456	5.755375	1.805645	0.596921	1.223791

4. Discussion and Implications

4.1. Discussion

As a result of China's rapid development in recent years, significant changes in China's CO_2 emissions and air quality have occurred. Tourism is inextricably linked to both. However, previous studies mainly focus on the unilateral impact of tourism on CO_2 emissions. Therefore, a better understanding of the relationship between CO_2 emissions, air pollution, and tourism flows is essential. This will allow policymakers to identify how tourism flows affect CO_2 emissions and how CO_2 emissions and air pollution affect tourism flows. This knowledge will provide a solid scientific basis for Chinese policymakers to implement specific sustainable tourism development policies. Therefore, this study quantitatively investigated the relationship between CO_2 emissions, air pollution (proxied by PM2.5 concentration levels, PM10, and SO_2 emissions), and tourism flows (inbound and domestic tourist arrivals) using panel data for 30 Chinese provinces from 2010 to 2017.

The results of this study suggested that there is a long-term equilibrium relationship between CO_2 emissions, air pollution, and tourist arrivals. Moreover, we found that the effect of CO_2 on inbound and domestic visitors was reversed. When other factors were held constant, a 1% increase in CO_2 emissions was associated with a 0.17% decrease in inbound tourists and a 0.41% increase in domestic tourists, which indicates that an increase in CO_2 emissions has a negative impact on inbound tourist arrivals and a positive impact on domestic tourist arrivals. The different impacts of CO_2 may be due to the inconsistency in destination choice and preference of inbound and domestic tourists. The impact of warming caused by CO_2 is different for different tourist destinations; for low latitudes and coastal areas, the increase in temperature will lead to longer summers, higher temperatures, and more extreme weather such as hurricanes [48,49], which will lead to a decrease in tourist arrivals. High latitudes, on the other hand, will attract more tourists due to the rising climate. Most of the destinations of inbound tourists are coastal regions and low-latitude regions of China; after the decrease in the attractiveness of these regions, the increase in CO_2 will negatively impact inbound tourist arrivals. Whereas the destination choice of domestic tourists does not show the same strong preference for coastal regions as foreign tourists, higher temperatures will make western China and high-latitude regions more attractive, thus increasing domestic tourists. Similar results were found by Grillakis et al. (2016). They found that climate change will positively impact tourism in central and northern Europe, increasing the potential for further development in this direction. Mediterranean countries may lose favorable tourism conditions during the hot summer months [54].

While previous studies have generally ignored the impact of differences in visitor sources on CO_2 emissions, this study examined the differential impact of inbound and domestic tourist arrivals on CO_2 emissions. Our results suggested that the number of domestic tourist arrivals has a greater significant impact on CO_2 emissions than the number of inbound tourist arrivals in China. This is because the number of domestic tourists in China is significantly higher than the number of inbound tourists, about four times higher than inbound tourists in 2017. In addition, an increasing number of domestic tourists choose to travel by car, leading to an increase in CO_2 emissions [52,53]. In addition, our results suggest a bidirectional causality between CO_2 emissions and domestic tourist arrivals, demonstrating an interaction between the two.

In our analysis of the impact of air pollution on tourist flows, PM2.5 was found to have a negative effect on inbound tourist arrivals but no significant effect on domestic tourist arrivals. This finding is novel and inconsistent with some previous studies, such as that of Xu et al. (2019) [35], which found that PM2.5 hurt domestic and inbound tourism. Possible reasons for this are as follows. The first reason is related to perception and concern about air pollution among different visitor groups. People's perceptions of the severity of air pollution largely depend on their education, knowledge, and income [55]. It is likely that, on average, the socio-demographic characteristics of inbound tourists make them more

concerned about PM2.5 than domestic Chinese tourists. Since inbound tourists typically stay longer than domestic tourists [35], inbound tourists are likely to be exposed to more PM2.5 when visiting polluted regions. Therefore, inbound tourists may be more responsive to changes in pollution. In addition, we found bidirectional causality between PM10 and inbound tourist arrivals and PM10 and domestic tourist arrivals. Moreover, PM10 has the strongest power in explaining innovations in inbound and domestic tourist arrivals in the long term. This may be due to the fact that PM10 is associated with a very pronounced effect on visibility compared to other air pollutants. By reducing visibility, PM10 can affect the aesthetics of tourist attractions and disrupt traffic [35,56], thus impacting domestic and inbound tourist arrivals on a long-term scale.

4.2. Implications

The results obtained in this paper are expected to contribute to the design of sustainable tourism policies. First, we found that CO_2 emissions and air pollutants such as PM2.5, PM10, and SO_2 have a negative impact on tourism arrivals. Therefore, China should pay attention to the pressure of CO_2 emissions and air pollution on tourism and further carry out emission reduction and air pollution control actions to reduce their negative impacts on tourism. In addition, the statistical results of this study show that the growth of inbound tourism in China has been very slow. We found that inbound tourist arrivals are more sensitive to the air pollution problem in China than domestic tourist arrivals. Therefore, in order to attract more international tourists, the air pollution problem should also be addressed. Since Beijing's air quality problems have attracted much international attention in recent years, inbound tourists may think that other Chinese cities also have poor air quality when, in fact, many Chinese tourist cities meet air quality standards [35]. Destination marketers in China can make efforts to promote these cities to potential inbound tourists. Second, we found a positive effect of tourism arrivals, especially domestic tourism arrivals, on CO_2 emissions. Therefore, to reduce environmental damage in the tourism sector, the government should raise environmental awareness of sustainable tourism among the domestic public through various channels such as media, advertisements, and newspapers [17,57]; develop tourism infrastructure and other infrastructure services in an environmentally friendly manner; and actively promote low carbon tourism. Third, we found that CO_2 emissions positively impact the number of domestic tourists, which may result from climate change, causing more people to shift to non-eastern coastal regions for tourism. Therefore, the tourism industry and related organizations on the eastern coast should be urged to develop and implement strategies to cope with the loss of tourists due to climate change.

5. Conclusions and Directions for Future Research

This study quantitatively investigated the relationship between CO_2 emissions, air pollution (PM2.5 concentration levels, PM10, and SO_2 emissions), and tourism flows (proxied by inbound and domestic tourist arrivals) using panel data for 30 Chinese provinces from 2010 to 2017. The results show the existence of a long-term equilibrium relationship between CO_2 emissions, air pollution, and tourist arrivals. A 1% increase in CO_2 emissions was associated with a 0.17% decrease in inbound tourists and a 0.41% increase in domestic tourists. PM2.5 level and PM10 and SO_2 emissions all had a negative effect on the number of tourists. Domestic tourist arrivals had a more significant influence on CO_2 emissions than inbound tourist arrivals in China. There was bidirectional causality between CO_2 emissions and domestic tourist arrivals. This means that CO_2 emissions and the number of domestic tourists have a two-way effect. A one-way causality running from PM2.5 to inbound tourist arrivals and from SO_2 emissions to domestic tourist arrivals was found. Moreover, we also found bidirectional causality between PM10 and inbound tourist arrivals and PM10 and domestic tourist arrivals. The variance decomposition function results suggest that PM10 and SO_2 emissions have stronger effects on inbound tourist arrivals in the long term, while CO_2 emissions and PM10 have stronger power in explaining innovations

in domestic tourist arrivals. The movements in domestic tourist arrivals did significantly affect CO_2 emissions in the long run.

The study in this paper suffers from several limitations, but these also provide promising directions for future research. First, some other air pollutants, such as CO (carbon monoxide), O_3 (ozone), and NO_2, were not investigated due to limitations of data availability. In the future, if more data can be collected, the effects of other air pollutants can be examined. Secondly, due to data limitations, the latest year for which all data could be collected in this paper is only up to 2017; however, many studies have shown significant improvements in AQI in the post-COVID-19 scenario. COVID-19 is also one of the biological and environmental parameters that have significantly reduced tourism activities not only in China but worldwide. We can study the relationship between COVID-19, air pollution, CO_2 emissions, and tourism when more data are released in the future.

Author Contributions: B.Z.: data curation; methodology; software; writing—review and editing; J.W.: writing—original draft; formal analysis; writing—review and editing; C.Z.: writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Key Laboratory of Sustainable Development of Historical and Cultural Tourism in Xinjiang, grant number 2020D04105.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Publicly available datasets were analyzed in this study. This data can be found here: http://www.stats.gov.cn/tjsj/ndsj/ (accessed on 13 May 2021), https://www.ceads.net/ (accessed on 13 May 2021), http://meicmodel.org (accessed on 30 September 2021).

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

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