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Research article

Air pollution and tourism development: An interplay

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ABSTRACT

We empirically examine the interplay between air pollution and tourism development based on a fine-grained dataset covering monthly-level tourism information of 58 major cities in China from October 2013 to December 2017. We adopt an empirical strategy utilizing wind speed as an instrumental variable for air pollution to deal with the endogeneity caused by the reverse causality. We control for individual city fixed effects, month fixed effects, meteorological conditions and other social factors of tourism destinations. We find the interplay between air pollution and tourism development. Our study offers significant empirical evidence for policy makers to design policies that can mitigate the consequences of air pollution in the tourism sector and manage the development of the tourism economy.

Introduction

The relationship between air pollution and tourism development has attracted much research attention but been less effectively examined in tourism literature. The key reason for this is that there is an interplay between the two – while air pollution in destination cities can affect tourists' decisions, tourists' consumption behavior in destination cities can reversely affect local air quality. Examining this interplay requires a complex empirical strategy based on high-quality data, which is a major limitation in prior studies. The motivation of our study is thus to address this issue. We aim to derive a clear picture of the interplay between air pollution and tourism development.

The empirical setting of our study is China, the world's largest emerging economy. Tourism is a pivotal sector for economic growth and job creation in China. According to the Ministry of Culture and Tourism of the People's Republic of China, in 2018 the comprehensive contribution of tourism accounted for 11.04% of GDP in China, and the direct and indirect employment in the tourism industry contributed to 10.29% of the country's total employment. However, the development of China's tourism economy is confronted with a significant challenge – a deficit caused by the imbalance between outbound and inbound tourism. Compared with the prosperity of outbound tourism, China's inbound tourism has been struggling during the past few years. According to statistics released by the United Nations World Tourism Organization, from 2010 to 2018 China's outbound tourism expenditure rose from 54.9 to 277.3 billion USD whereas its inbound tourism receipts declined by 5.4 billion USD (from 45.8 to 40.4). China's tourism deficit reached 236.9 billion USD in 2018.

Although such a deficit in China's tourism industry was caused by a series of economic and non-economic factors both home and abroad, many scholars believed that China's environmental issues (particularly its air quality) were a significant factor (Becken et al., 2017; Zhou et al., 2019). Such a claim was also supported by media accounts. According to the World Health Organization's (WHO)

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standards, China's average particulate matter 2.5 ($PM_{2.5}$) concentration is up to four times the pollution level of countries in Europe and the United States (Chang et al., 2016). Beijing once reached a $PM_{2.5}$ concentration value that was around 40 times the WHO's maximum guideline. Severe air pollution has locked international tourists out of China (Dong et al., 2019a) and forced Chinese tourists to go overseas (Wang et al., 2018).

It is a natural view that air pollution affects tourism development, i.e., tourists refrain from sightseeing in cities where air quality causes health concerns. But reversely, the development of tourism can also affect the quality of the air in destination cities. Destination cities with famous attractions (e.g., Beijing and Xi'an) can host a huge number of tourists annually. Tourists' overall consumption during high-tourism periods can noticeably affect the quality of the air in destination cities. Therefore, there clearly is an interplay between air quality and tourism development in China. Understanding the interplay between air pollution and tourism development empirically can offer significant policy implications for the tourism economy in China.

Examining such a complex interactive relationship requires us to adopt a sophisticated empirical strategy based on high-quality data. To date, in the literature, there is no research simultaneously (1) examining the interplay between air pollution and tourism development using fine-grained high-quality data and (2) dealing with the endogeneity caused by the reverse causality between the two. In this study, we compile a fine-grained dataset covering monthly-level information about tourist arrivals, tourism receipts, air quality, hotels, attractions, weather conditions, and other factors of 58 major cities in China from October 2013 to December 2017. We adopt an empirical strategy utilizing wind speed, an exogenous meteorological condition independent of economic activities, as an instrumental variable (IV) for air pollution to deal with the endogeneity caused by the reverse causality. We control for individual city fixed effects, monthly fixed effects, meteorological conditions, and other social factors of tourism destinations. The contribution of our research is twofold. Empirically, we derive robust evidence of the interplay between air pollution and tourism development, thus offering significant empirical findings for China to design policies that can mitigate the consequences of air pollution in the tourism sector and manage the development of tourism economy. Methodologically, we further test the validity of using wind speed as an IV for air pollution to deal with endogeneities, an approach that becomes popular in economics literature. We for the first time introduce this approach to tourism literature.

Literature review

Searching through the literature comprehensively, we have identified several empirical studies that are relevant to the relationship between air pollution and tourism management. We summarize these studies according to their data sources, methods and empirical findings in Table 1. These empirical studies can be grouped into three strands of research. A first strand finds that there is no relationship between air pollution and tourism. Law and Cheung (2007) collected the views of 1304 international visitors through a survey and found that international visitors to Hong Kong had a neutral view about air quality when they made their travelling decisions. In other words, air quality was not a key factor influencing tourists' behavior. Similarly, using a fixed effect panel model and comparative analysis, Sun et al. (2019) found that there was no significant effect of haze concentration on domestic travel based on the data of 28 major cities in China.

A second strand finds that air quality plays a vital role in tourists' decisions, thereby affecting tourism development. Becken et al. (2017) conducted a survey involving 600 US and Australian residents. Using structural equation modelling the authors suggested that feelings about air quality and affective risk perception negatively affected international tourists' intention to visit China. Zhou et al. (2019) adopted a gravity model, and using a case study of Bejing, the authors found that air quality had a significant negative impact on China's inbound tourism. A more recent study Dong et al. (2019a) based on data of 274 Chinese cities covering the period 2009–2012 found that air pollution significantly depressed international inbound tourism to China.

A third strand, reversely, examines the effect of tourism development on air quality. Many studies found that air pollution was a core external cost in tourism, and the contribution of tourists' behavior to air pollution could not be ignored (Sáenz-de-Miera and Rosselló, 2013, 2014). Lenzen et al. (2018) claimed that the tourism industry was responsible for 8% of greenhouse gas emissions on the earth. Sáenz-de-Miera and Rosselló (2014) found that a 1% rise in tourist numbers could cause a 0.45% increase in PM_{10} concentration. Interestingly, within this strand of research, some other scholars held an opposite view, suggesting that tourism had negative effect on CO_2 emissions based on the investigation in the EU (Lee and Brahmasrene, 2013), Singapore (Katircioğlu, 2014), and China (Zhang and Gao, 2016). From Table 1 we can see that prior studies adopted diverse proxies and empirical methods to study the relationship between air pollution and tourism development. However, these studies were uni-directional, i.e., they studied either the effect of air pollution on tourism development or the effect of tourism development on air pollution without considering the endogeneity caused by the reverse causality between two.

To advance our understanding of the relationship between air pollution and tourism development, we develop the interplay view, i.e. a bi-directional influence between air pollution and tourism development, based on prior empirical evidence. In our empirical strategy, we use wind speed as an IV for air pollution to examine the effect of air pollution on tourism development. We then discuss the interplay between air pollution and tourists based on our empirical results.

Sample, variables and models

Data source

We start our sampling by looking at all 285 prefectural-level cities in China. As our data covers multiple variables (e.g. tourist arrivals, tourism receipts, air quality, hotels, attractions, weather conditions and other factors), we gradually filter out some cities

Table 1
Summary of prior studies related to air quality and tourism development (in reverse chronological order).

Study	Data	Methods	Findings
Xu et al. (2020)	Panel data on 174 prefecture-level cities in mid-eastern China from 1998 to 2016	Spatial Durbin model (SDM); Geographical weighted regression (GWR)	Both haze pollution and inbound tourism growth in mid-eastern China have apparent spatial autocorrelation and significant spatial spill-over effects
Dong et al. (2019b, b)	Panel dataset covering 337 Chinese cities from 2004 to 2013	Spatial Durbin model (SDM)	Air pollution significantly reduces domestic tourist arrivals in the local cities; air pollution demonstrates significant spatial spill-over effects; the magnitude of the spill-over effects of air pollution is larger than the negative direct effects on local cities.
Dong et al. (2019b, b)	274 Chinese cities during the period 2009–2012	Regression discontinuity design (RDD); quasi-experiment generated by China's Huai River Policy	Air pollution significantly reduces the international inbound tourism
Guo et al. (2019)	31 provinces of China for the period 2012–2015	bootstrapped truncated regression model	Visible air pollutants significantly decrease the operational efficiency of China's hotel industry, while invisible air pollutants insignificantly affect the hotel industry.
Liu et al. (2019)	Panel data from the 17 underdeveloped provinces of China for 2005–2015	Panel data regression	$PM_{2.5}$ concentration has a negative impact on domestic visitors but an insignificant impact on international visitors.
Sun et al. (2019)	28 main Chinese cities (1999 to 2015)	two-way fixed effect panel model	There is no significant effect of haze concentration on domestic travel, but public awareness of this air problem has a significant and positive effect on that.
Zhou et al. (2019)	31 administrative units were taken as the domestic origins and analysed together with 24 major inbound source markets between years 2005 and 2016	A gravity model, in which air quality variables are incorporated into the model of tourism demand.	Air pollution has a negative influence on tourism flows and that this effect is more pronounced for inbound than for domestic tourism.
Azam et al. (2018)	World Development Indicators (2016) data set of Malaysia, Singapore and Thailand for the period of 1990 to 2014.	Multivariate model, Zivot–Andrews test; Fully Modified Ordinary Least Squares estimator	Tourism has a significant positive effect on environmental pollution in Malaysia. However, an inverse relationship between tourism and environmental pollution is observed in Thailand and Singapore.
Lenzen et al. (2018)	Quantify tourism-related global carbon flows between 160 countries from 2009 to 2013.	A comprehensive calculation of the carbon footprint of global tourism	Tourism's global carbon footprint has increased from 3.9 to 4.5 GtCO2e, four times more than previously estimated, accounting for about 8% of global greenhouse gas emissions.
Lu et al. (2018)	Qingyang Gansu Province, China, from 1990 to 2017	The Vector Auto Regression (VAR)-based coupling model; the econometric model based on the curse effect	The development of the tourism industry not only imposes a direct negative influence on the environment, but also adversely affects it in an indirect way through its influence over some mediating factors.
Wang et al. (2018).	Transaction data from a leading online travel agent (OTA) in China in 2015.A city-day level panel dataset (with 11 cities 366 daily observations)	Ordinary Least Square (OLS) regression	Air quality in the place of origin creates a pushing effect as local outbound tourism demand increases as air quality deteriorates. This relationship is negatively moderated by local disposable income level.
Wang and Wang (2018)	35 OECD countries with annual data over the period 1995–2014	IPS; Fisher ADF tests; Fisher-PP tests; Hausman test; method of Pesaran; test of De Wachter and Tzavalis	Tourism growth raises more CO2 emissions in the future, and that greater CO2 emissions return a lagged and negative impact on tourism development.
Zhou et al. (2018)	Monthly data of 24 Chinese cities from January 2007 to December 2012.	Corrected least square dummy variable (CLSDV); system-GMM and difference-GMM	Air pollution in China adversely impacts inbound tourism demand; there is a lagged effect of air pollution.
Becken et al. (2017)	Online panel survey of 600 US and Australian residents.	Structural equation modelling (SEM)	Feelings towards the risk of air quality had a significant negative impact on destination image as well as intention to visit China.
Chen et al. (2017)	Monthly time series data of the number of visitors starting from January 2004 to December 2011 in Taiwan	Markov regime-switching approach	The effects of air pollution and rainfall on the demand for tourism depend significantly on the phases of business cycle
Deng et al. (2017)		Spatial Durbin model	

(continued on next page)

Table 1 (*continued*)

Study	Data	Methods	Findings
	Panel data on 31 Chinese provinces during the period 2001–2013.		Air pollution has a significant direct negative effect on international tourists visiting China; Air pollution in the neighbouring provinces has a significant negative impact on international tourist arrivals in the local province. The spill-over effect is even larger than the direct effect.
Dogan and Aslan (2017)	25 EU and candidate countries; The annual data are from 1995 to 2011.	Econometric methods	Energy consumption contributes to the level of emissions while real income and tourism mitigate CO2 emissions.
Xu and Reed (2017)	Use Google Trends data to measure perceived pollution in China, monthly data during 2006–2014	VAR model	Perceived pollution lowers inbound tourism.
Li et al. (2016)	Face-to-face contact at the Summer Palace, one of the major tourist attractions in Beijing on 5 June 2014, 126 usable questionnaires were collected.	Structural equation model	Direct relationships were found for the hypothesized effects of smog concern on risk perception and satisfaction. Further, the influence of risk perception on reducing satisfaction and the role of satisfaction in forming revisit intention (loyalty) were identified.
Zhang and Gao (2016)	Balanced panel data set of 30 provinces in China over the period 1995–2011.	Panel unit root tests; Panel cointegration tests; Panel Granger causality	Tourism has a negative impact on CO_2 emissions in the eastern region in china
Katircioglu (2014)	Annual figures covering the period 1960–2010 in Turkey	Econometric analysis; unit-root test; bounds test	Tourism in Turkey exerts positive and statistically significant effects on CO_2 emissions in the long-term and shorter periods.
Katircioğlu (2014)	Singapore, annual figures covering the period 1971–2010	The second generation econometric procedures that take multiple structural breaks into consideration have been adapted to the study through GAUSS codes.	Tourist arrivals have significant negative effects on CO_2 levels both in the long-term and the short-term periods; there is unidirectional causality that runs from tourism development to carbon emission growth in the long-term of the economy of Singapore.
Katircioğlu (2014)	The case of Cyprus, annual figures covering the period 1970–2009.	Econometric analysis; unit-root test; bounds test; Granger causality tests	International tourist arrivals have positive, statistically significant, and inelastic impacts on the level of energy consumption and CO_2 emission.
Sajjad et al. (2014)	South Asia, the Middle East and North Africa, sub-Saharan Africa, and East Asia and the Pacific regions, over a period of 1975–2012	Dickey–Fuller (ADF) technique; estimate vector autoregression (VAR) model, and autoregressive distributed lag model (ARDL)	Climatic factors and air pollution affect the tourism industry; however, the intensity to affect the tourism indicators varied region to region
Sáenz-de-Miera and Rosselló (2014)	Data on PM10 concentrations were obtained from the Consell de Mallorca and are available from two monitoring stations, Bellver and Foners. The time series range from 1 January 2003 to 31 December 2007	Generalized Additive Model	A 1% increase in tourist numbers can be related to up to a 0.45% increase in PM_{10} concentration levels.
Lee and Brahmasrene (2013)	Panel data of European Union countries from 1988 to 2009	Panel cointegration techniques and fixed-effects models	Tourism and foreign direct investment (FDI)incur a high significant negative impact on CO2 emissions.
Poudyal et al. (2013)	Monthly visitation data of Great Smoky Mountain National Park (GSMNP) in USA	Polynomial distributed lag model	Improve the average visibility by 10% (5.5 km) from the current level could result in an increase of roughly one million recreational visits annually.
Sáenz-de-Miera and Rosselló (2013)	Case study of Mallorca (Spain); the time series range was from January 1, 2003 to December 31, 2007	linear and non-linear model	Rising tourism activity in Mallorca is associated with rising daily concentrations of tropospheric ozone, created by transport, air conditioning and other activities.
Law and Cheung (2007)	Survey 1304 international travellers	*t*-test	The respondents generally did not perceive the air quality in Hong Kong as a concern when they chose to travel; they had a neutral view of this issue.

according to the data availability, and finally we gain a sample composed of 58 major Chinese cities. We compile a panel dataset covering the period from October 2013 to December 2017. The unique dataset covers information about air pollution, tourism development indicators, and weather conditions, etc. collected from various highly credible sources.

In 2011, the China National Tourism Administration (CNTA) issued the Program on the System of Improving Domestic Tourism

Statistics that required every region to establish an effective statistical indicator system for its tourism. From July 2011 to August 2013, 23 provinces in China joined the pilot of this program. In 2014, CNTA issued the new Evaluation Method of Domestic Tourism Statistical Indexes throughout the country, which clarified the six main statistical indicators used for the Chinese domestic tourism. In this context, the information regarding Chinese tourism development is now transparent and standardized, and tourism development data can be conveniently obtained.

We intend to use the number of tourists and the income generated by tourism to measure the development of tourism in Chinese cities. According to the basic statistical index system, the total number of domestic and foreign tourists reflects the scale of tourism development in a given city, and the total income of tourism in that city is the core index that we use to reflect the economic benefits of tourism. Therefore, we can measure the tourism development of the city using these two indicators.

Variables

Dependent variables

Tourists. It is the total number of domestic and foreign tourists who visit a given city. The number of monthly tourists, in the form of a normalized index, comes from the website of the city's Bureau of Statistics and Tourism Administration. The number includes overnight tourists and one-day tourists. The tourist data covers 58 sample cities for the period from October 2013 to December 2017 on a monthly basis.

Income. It is the total income that tourism brought to the city. The data about total tourism income also comes from the city's Bureau of Statistics and Tourism Administration website. It should be noted that the monthly tourism income from foreign tourists is converted into RMB according to the average exchange rate during the given month.

Independent variables

AQI. This term is the Air Quality Index (AQI). Station-level hourly AQI can be obtained from the website of the Ministry of Ecology and Environment of the People's Republic of China. The main pollutants involved in the calculation of AQI include NO_2, SO_2, PM_{10}, $PM_{2.5}$, CO and O_3. Compared with other air pollution indexes, e.g. Air Pollution Index (API) which only involves NO_2, SO_2 and PM_{10} and is released once a day, AQI is more precise and stricter. We work out a sample city's monthly average AQI according to its hourly site data and use this AQI as the core independent variable. The time period covers Oct 2013 to December 2017.

$PM_{2.5}$. This is the fine particulate matter. It can levitate in the air for a long time, and the higher the concentration in the air, the more serious the air pollution. $PM_{2.5}$ data also comes from the website of the Ministry of Ecology and Environment of the People's Republic of China. According to the Global Environmental Outlook 5 published by the United Nations Environment Program in 2012, nearly 2 million premature deaths each year are related to $PM_{2.5}$. Previous studies have shown that $PM_{2.5}$ can have a negative impact on people's physical and mental health. Therefore, we choose a sample city's monthly average $PM_{2.5}$ as an alternative variable to AQI for the robust test.

Control variables

Weather. Becken and Wilson (2013) studied the impacts of weather on tourist travel using a sample of international tourists visiting New Zealand during the 2009–10 summer season and derived robust empirical evidence that weather conditions can change tourists' travel behavior. Since weather affects the behavioral decisions of tourists, it is necessary to control for the influence of weather. The variables used in this paper include precipitation (in 0.01 mm increments), temperature (in 0.01 degree centigrade increments), sunshine duration (in 0.1 h increments), and relative humidity (in 1% increments). Weather data is collected from the National Climatic Data Center of the China Meteorological Administration. Weather data for our analysis covers 51 weather stations, on an hourly basis from October 2013 to December 2017. If the monitoring point is not located in a given sample city, we choose the data from its nearest monitoring point to collect the data. All weather variables are monthly averages at city level.

Holiday. People tend to travel during established (state, national, governmental, etc.) holidays, which reflects the influence of leisure time on the behavioral decisions of tourists. Holiday in our study is a dummy variable, which, in addition to weather, has an inevitable impact on tourism development. When a month includes established holidays, its value is 1; otherwise its value is 0.

Instrumental variable

Wind speed. Wind speed (in 0.1 miles per hour increments) is derived along with other weather condition variables we control for. But here we use it as an instrumental variable for air pollution. Justifications for this are specified in our empirical strategy. Wind speed data is a monthly average at city level.

Descriptive statistics

The original dataset includes 2370 observed values. The maximum number of tourists is 104.7 million, and the minimum number in is 30,300; the average number of tourists is 4.86 million. The highest and lowest total incomes of tourism are 150 billion RMB and 0.03 billion RMB, respectively. The city with the lowest tourist income earned 175 times less in tourism income than the average. The descriptive statistics of the key variables used in the empirical analysis are reported in Table 2.

Table 2
Descriptive statistics.

Variable	Label	N	Mean	SD	Min	Max
Visitors	Number of tourists	2370	486.087	730.883	3.03	10,469.35
Income	Tourism revenue	2370	526,587.2	781,242.8	3043.63	15,000,000
AQI	Air quality index	2370	72.6566	27.906	20.1936	227.1613
$PM_{2.5}$	$PM_{2.5}$	2370	45.5721	24.0037	5.4516	184.097
PRE	Average precipitation	2370	42.8191	41.9914	0	307.7667
TEMP	Average temperature	2370	175.9863	85.4598	−130	318.1613
SSD	Average sunshine duration	2370	50.5133	20.3597	0	116.7419
RHU	Average relative humidity	2370	74.2519	11.2785	21.9355	95.9355
SPD	Average wind speed	2370	21.9846	8.4063	5.9333	82.0645
HOL	Holiday	2370	0.8114	0.3913	0	1

We work out the monthly average AQI for all sample cities from October 2013 to December 2017. The distribution of AQI levels for all sample cities from October 2013 to December 2017 is shown in Fig. 1. On average, only 20% of months during the sampling period reached the optimal air quality level; the optimal air quality level is regarded as "excellent" with an AQI below 50. In comparison, over 14% of months during the sampling period were "lightly polluted", and nearly 3% of the months during the sampling period were classified as "moderately polluted" or "heavily polluted" with an AQI over 150. Fig. 2 displays the distribution of AQI and $PM_{2.5}$ for the sample cities in January 2017. Generally speaking, the central, southern and northeast regions were heavily polluted.

The tourism development data (i.e. monthly number of tourists and monthly tourism income) shows that the development of Chinese tourism is extremely unbalanced. In addition, many cities still have great potential for the development of a tourism economy. Local governments can fully develop their local tourism resources and respond to the motto that "clear waters and green mountains are as good as mountains of gold and silver" proposed by top political leaders in the central government. They could also fully develop tourism from the perspective of the environment, making new economic growth.

Empirical strategy

The development of tourism may damage the local ecological environment, and the improvement of a tourism economy is likely to aggravate air pollution (Azam et al., 2018; Zhong et al., 2011). However, air pollution (e.g. smog) in tourist destinations can enable tourists to change their travel behavior and have a negative impact on the development of local tourism. Thus, there is a clear two-way causal relationship between air pollution and tourism development, which causes endogeneity in regression models that we must handle. Therefore, we choose the instrumental variable method to solve the endogeneity concern. We select the average wind speed as an instrumental variable (IV) for air pollution. Becken (2013) found that the wind speed in an area has no direct impact on local

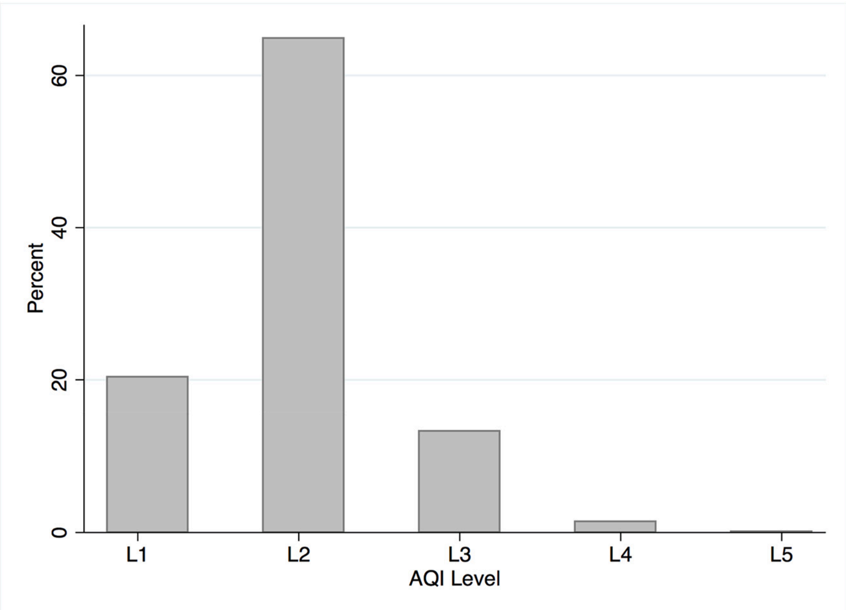
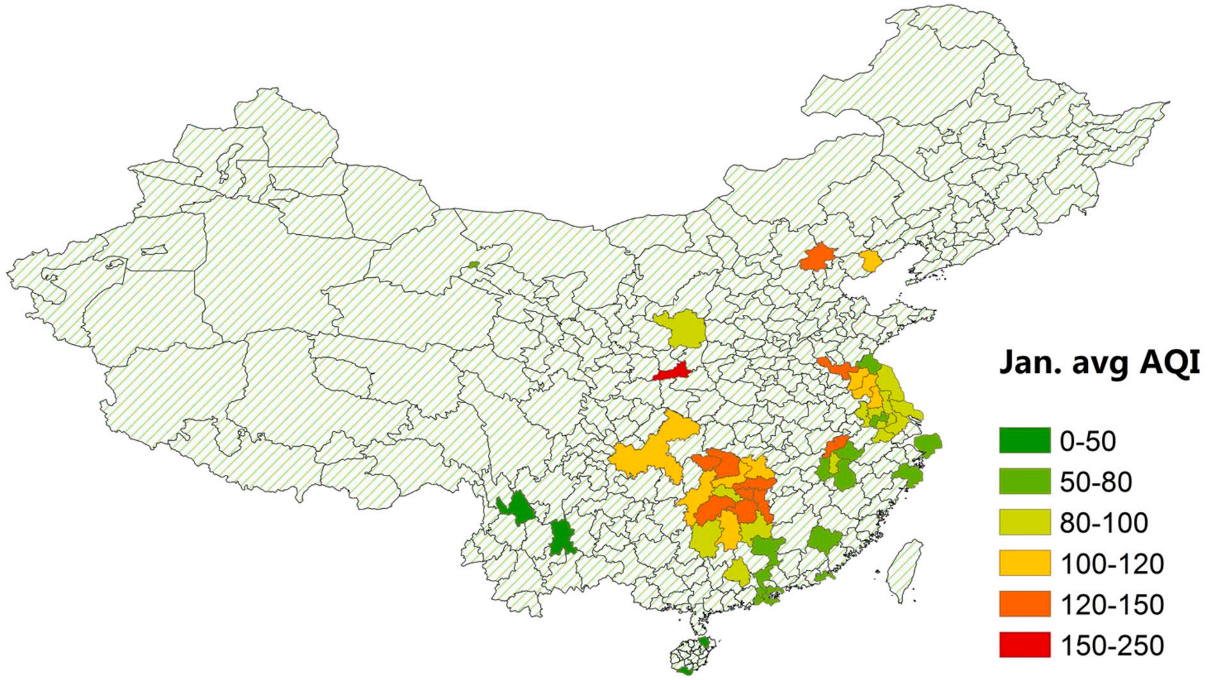


Fig. 1. AQI Level. This figure depicts the percentage of months during the sampling period falling into each level of air quality, with L1 being the best quality and L5 being the worst. The monthly pollution data cover all sample cities from October 2013 to December 2017.



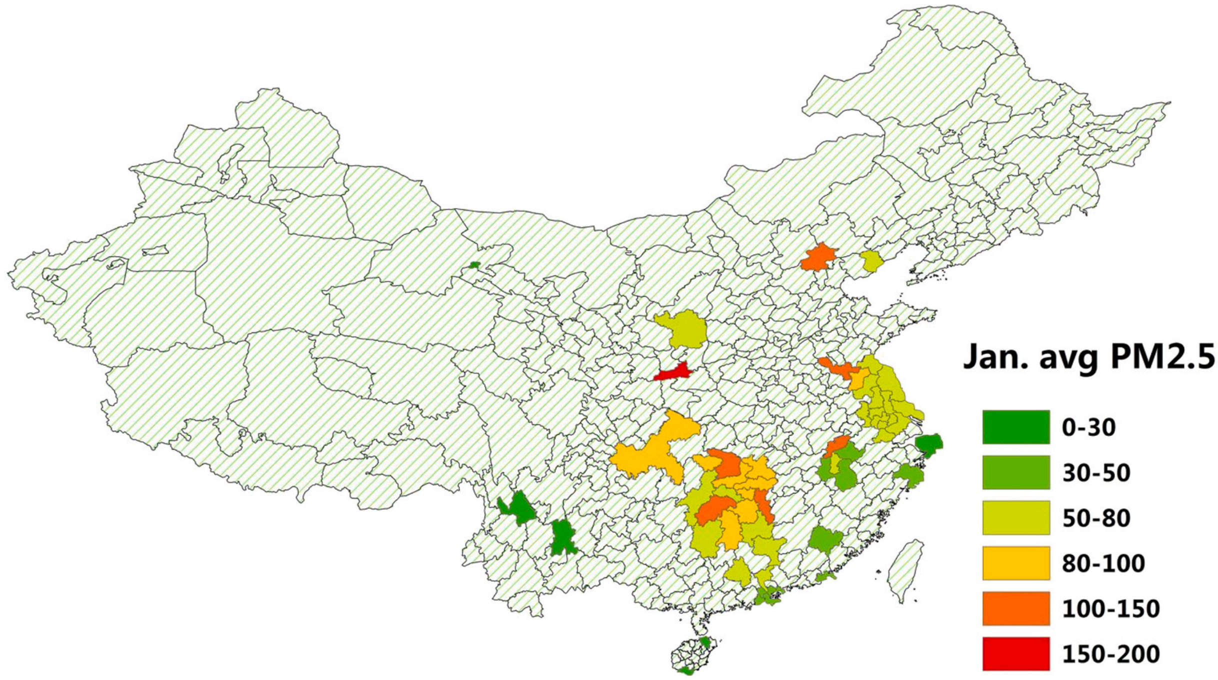


Fig. 2. Mean AQI and $PM_{2.5}$ concentrations($\mu g/m^3$) in January 2017. The data is based on the January 2017 mean concentrations of 54 monitoring stations.

Table 3
The effect of average wind speed on air pollution (First Stage).

Variable	(1) AQI	(2) $PM_{2.5}$
Average wind speed	−0.6062***	−0.5957***
	(0.2059)	(0.1665)
Weather	Yes	Yes
Holiday	Yes	Yes
Month FE	Yes	Yes
City FE	Yes	Yes
F-statistics	81.10	90.03
N	2370	2370

Robust standard errors are in the parentheses.
*** $p < .01$.
** $p < .05$.
* $p < .10$.

tourism. However, wind speed is closely related to air quality, because it contributes to the clearance of pollutants. Fine particles in the air have very small mass, and very small wind may have a huge impact on the clearance of smog (Campbell and Gipps, 1975; Mossetti et al., 2005). For the estimation, we use the Generalized Method of Moments (GMM) to overcome possible autocorrelation and heteroscedasticity of the panel data. The econometric regression models are as follows:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln P_{it} + \beta_2 X_{it} + \lambda_i + \delta_t + \varepsilon_{it} \tag{1}$$

$$P_{it} = \alpha_0 + \alpha_1 I_{it} + \alpha_2 X_{it} + \lambda_i + \delta_t + \mu_{it} \tag{2}$$

In the above models, Y_{it} is the tourism development indicator for city i in month t; P_{it} is the air pollution indicator (i.e. AQI or $PM_{2.5}$) for city i in month t; X_{it} is the control variable such as weather or holidays for city i in month t; I_{it} is the instrumental variable, i.e., the average wind speed for city i in month t; λ_i is the city fixed effect; δ_t is the month fixed effect; ε_{it} and μ_{it} are the error terms, and α and β are the regression coefficients.

Table 3 presents the estimates of the effect of the average wind speed on air pollution using city and month fixed effects. Column (1) shows the effect of average wind speed on AQI, and Column (2) displays the effect of average wind speed on $PM_{2.5}$. We find significant and robust negative effects of average wind speed on both air pollution measures. The higher the average wind speed, the smaller the air pollution indicators, and the better the air quality. The results show that a 1 unit increase of the average wind speed will lead to a 0.61 unit decrease of AQI and a 0.6 unit decrease of $PM_{2.5}$. The F-statistics are 81.10 and 90.03 for the two models, suggesting that there is no weak IV concern. The results prove that monthly average wind speed is an appropriate instrumental variable for air pollution.

Empirical analysis and results

Interplay between air pollution and tourism development

We run separate regressions for the total number of tourists and the total income of tourism of a city. The estimation results are presented in Table 4. Columns (1) and (3) report the OLS estimates of Eq. (1), while Columns (2) and (4) report the IV estimates. Panels A and B show the effects of AQI and $PM_{2.5}$, respectively. They both use city fixed effect and month fixed effect, and control for the influence of the weather and holiday factors on tourism.

The results of IV estimates (Columns (2) and (4) in Table 4) show that a 1% point increase in the AQI leads to a 1.25% point decrease in the total number of tourists in a city, and a 1.13% point decrease in the total income generated by tourism in a city. Both estimates are statistically significant at the 0.01 level. Overall, the empirical results show that air pollution can negatively affect the tourism economy of a city.

A comparison between the OLS estimates and the IV estimates in terms of coefficients can enable us to identify the interplay between air pollution and tourism development. The purpose of using IV estimate is to rule out the reverse causality between explanatory variables and response variables. For AQI➔Visitors, the coefficient of OLS estimate is −0.1751 ($p < .10$), and the coefficient of IV estimate is −1.2501 ($p < .01$). We can see that after we rule out the effect of the response variable Visitors on the explanatory variable AQI, there is a significant change of absolute value of the coefficient, which implies that there is a strong reverse causality between Visitors and AQI. The same effect applies to AQI➔Income, $PM_{2.5}$➔Visitors, and $PM_{2.5}$➔Income. We, therefore, identify the interplay between air pollution and tourism development.

To further check the interplay, we run the original regressions reversely. Table 5 shows the results. We can clearly see that the effects of Visitors on both AQI (coefficient = 0.0220, $p < .05$) and $PM_{2.5}$ (coefficient = 0.0260, $p < .05$) are significant and positive, and the same effect applies to Income➔AQI (coefficient = 0.0191, $p < .05$) and Income➔$PM_{2.5}$ (coefficient = 0.0240, $p < .05$). Therefore, the interplay between air pollution and tourism development is robustly confirmed.

The interplay we find is generally in line with the empirical findings of Seetanah and Fauzel (2019), in which the authors studied the impact of climate change on the tourism sector using a sample of 18 small island economies over the period 1989–2016. Using a

Table 4
The effect of air pollution on tourism development.

	Visitors		Income	
	(1)	(2)	(3)	(4)
Panel A				
AQI	−0.1751*	−1.2501***	−0.2418**	−1.1285**
	(0.0885)	(0.4540)	(0.1038)	(0.4861)
Weather	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	2370	2370	2370	2370
Panel B				
$PM_{2.5}$	−0.1641***	−0.8238***	−0.2206***	−0.7437**
	(0.0603)	(0.2935)	(0.0704)	(0.3157)
Weather	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	2370	2370	2370	2370

Robust standard errors are in the parentheses.
*** $p < .01$.
** $p < .05$.
* $p < .10$.

Table 5
The effect of tourism development on air pollution (OLS estimates).

Variable	AQI		$PM_{2.5}$	
	(1)	(2)	(3)	(4)
Visitors	0.0220**		0.0260**	
	(0.0089)		(0.0123)	
Income		0.0191**		0.0240**
		(0.0077)		(0.0107)
Weather	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
F-statistics	84.44	84.44	100.95	100.98
N	2370	2370	2370	2370

Standard errors are in the parentheses.
*** $p < .01$.
** $p < .05$.
* $p < .10$.

dynamic panel data analysis method (i.e., a panel vector autoregressive (PVAR) framework), Seetanah and Fauzel (2019) found that "an increase in tourism leads to environment degradation and vice versa" (p. 200) from both the short-run and the long-run perspectives.

Nonlinear effect of air pollution on tourism development

Previously, we assumed that the dependent variables in Eq. (1) were constant. However, some studies have found that the effects of air pollution on economic variables tend to be nonlinear (e.g. He et al., 2019; Schlenker and Walker, 2015). Such interpretation in our study is that, compared with in scenarios where air quality is good, tourist behavior is more sensitive to air quality in scenarios where the air is polluted. Therefore, we allow the influence to be nonlinear in terms of AQI. We use five dummy variables in the model specification to indicate the six pollution levels defined by the Ministry of Ecology and Environment based on AQI in China (Level 1: < 50; Level 2: 51–100; Level 3: 101–150; Level 4: 151–200; Level 5: 201–300; Level 6: > 301). The nonlinear model is as follows:

$$\ln Y_{it} = \beta_0 + \sum_{k=1}^{5} \alpha_k D_{kit} + \beta_2 X_{it} + \lambda_i + \delta_t + \varepsilon_{it} \tag{3}$$

Table 6
The nonlinear effect of air pollution on tourism development.

Variable	(1) Visitors	(2) Income
Level 2	−0.0265	−0.0378
(51—100)	(0.0370)	(0.0443)
Level 3	−0.1278*	−0.1542*
(101—150)	(0.0678)	(0.0848)
Level 4	−0.5207***	−0.5841***
(151—200)	(0.1370)	(0.1628)
Level 5	−0.8384***	−0.7032***
(201 − 300)	(0.1065)	(0.1752)
Weather	Yes	Yes
Holiday	Yes	Yes
Month FE	Yes	Yes
City FE	Yes	Yes
N	2370	2370

Robust standard errors are in the parentheses.
*** $p < .01$.
** $p < .05$.
* $p < .10$.

In the above model, Y_{it} is the tourism development indicator for city i in month t; D_{kit} is the dummy variable; X_{it} is the control variable such as weather or holidays for city i in month t; λ_i is the city fixed effect; δ_t is the month fixed effect; and ε_{it} is the error term.

The nonlinear estimation results are shown in Table 6. Column (1) presents the estimation of the influence of air pollution levels on the total number of tourists, while Column (2) reports the estimation of the effect of air pollution levels on the total income of tourism. Please note there is no Level 6 in our study, as the largest value of AQI in our study is 227.1613. We can see that when the air quality is “good”, the effect of air pollution on tourism development is not statistically significant. However, when the air quality turns to “slightly polluted”, the effect of air pollution on tourism development becomes significantly negative. The worse the air quality is, the more negative the impact is.

To further examine the non-linear effect of air pollution on tourism development, we add a quadratic term of AQI into our regression model to depict the curve change of the tourism development index with the change in air quality. The model is as follows:

$$Y_{it} = \beta_0 + \beta_1 AQI + \beta_2 AQI^2 + \beta_3 X_{it} + \lambda_i + \delta_t + \varepsilon_{it} \quad (4)$$

We use the model to measure the inflection point of the effect of air quality on tourism development. When AQI reaches 54.29, the tourism indicators reach their peaks. In other words, when the air quality index drops from “excellent” to “good”, the tourism development begins to move downward. The results imply that the AQI should be controlled at the level of “good” in order to enable the local tourism economy to reach its optimal value.

Robustness tests

Controlling for potential threats

With our empirical strategy, we control for weather, holiday, city fixed effects, and month fixed effects. After controlling for these important underlying factors, some other possible sources of exogenous variations may still affect our estimation. Therefore, we need to address these potential threats which are detailed below.

Travel costs. Fluctuations in transport costs, ticket prices, and accommodation prices are not observable. Since these prices are relatively stable in a month, we use month fixed effect to control for these unobserved effects (Models 1 and 6 in Table 7). In addition, we also control for year-month fixed effect, taking into account the variations of factors such as discounts and/or promotions offered by destination cities in a month across different years (Models 4 and 9 in Table 7).

Comprehensive consumption attributes at the city level. These factors, e.g., household income, population, culture, and consumer price index, are either difficult to obtain or unobservable. These factors are related to air pollution and tourism development. To address them, we combine city-year fixed effect and year-month fixed effect (Models 3 and 8 in Table 7). Furthermore, we also combine city fixed effect and region-month fixed effect to address regional heterogeneity in six administrative regions in China (Models 5 and 10 in Table 7).

Marketing and infrastructure. We combine city-year fixed effect and month fixed effect to capture city characteristics that change year by year (Models 2 and 7 in Table 7). This approach can enable us to control for the impact of marketing activities and tourism infrastructure developments that changed over the years from 2013 to 2017 on the development of city tourism.

The results in Table 7 show that after we control for these potential threats, air pollution still has a significant negative impact on local tourism development and causes major losses to local tourism economy.

Table 7
The effect of air pollution on tourism development after controlling for potential threats (IV).

	Visitors					Income				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AQI	−1.2501***	−0.5293*	−0.5298*	−1.2507***	−1.2196***	−1.1285**	−1.6274***	−1.6276***	−1.1297**	−1.0999**
	(0.4540)	(0.3193)	(0.3193)	(0.4537)	(0.4531)	(0.4861)	(0.3756)	(0.3755)	(0.4857)	(0.4847)
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes			Yes	Yes	Yes			Yes	Yes
Month FE	Yes	Yes				Yes	Yes			
City-year FE		Yes	Yes				Yes	Yes		
Year-month FE			Yes	Yes				Yes	Yes	
Region-month FE					Yes					Yes
N	2370	2370	2370	2370	2370	2370	2370	2370	2370	2370

Robust standard errors are in the parentheses. City fixed effect is used to control for time invariant factors at city-level. Month fixed effect is used to control for time-varying factors at month-level. City-year fixed effect is used to control for time-varying unobservable effects at city-year level. Year-month fixed effect is used to control for time-varying unobservable effects at month-level year-by-year. Region-month fixed effect is used to control for time-varying unobservable effects at region-month level.
*** $p < .01$.
** $p < .05$.
* $p < .10$.

Intertemporal effect of air pollution on tourism development

All previous models assumed that tourists responded to air pollution information only at the time it was released. However, tourists may have time-lagged responses to air pollution information. Severe air pollution may result in the negative evaluation of a tourism experience, leading to a future decrease in the number of tourists and the income generated by tourism. Therefore, there is an intertemporal effect of air pollution on tourism development. We discuss the intertemporal issue using three lagged terms of AQI. The model is as follows:

$$\ln Y_{it} = \beta_0 + \sum_{k=1}^{3} \theta_k \ln P_{i,t-k} + \beta_2 X_{it} + \lambda_i + \delta_t + \varepsilon_{it} \tag{5}$$

In this model, Y_{it} is the tourism development indicator for city i in month t; $P_{i,t-k}$ is the lag of AQI; X_{it} is the control variable such as weather and holidays for city i in month t; λ_i is the city fixed effect; δ_t is the month fixed effect; and ε_{it} is the error term.

The intertemporal effect estimation results are shown in Table 8. Column (1) reports the estimates of the impact of air pollution on the total number of tourists, and Column (2) reports the estimates of the influence of air pollution on tourism income. We find that AQI can have a continuous negative effect on tourism development for two months. Additionally, one-month-lagged AQI has the largest effect on tourism development.

Table 8
The intertemporal effect of air pollution on tourism development.

Variable	(1) Visitors	(2) Income
AQI_t	−0.1751*	−0.2418**
	(0.0885)	(0.1037)
AQI_{t-1}	−0.2169**	−0.2193**
	(0.0912)	(0.1058)
AQI_{t-2}	−0.1220	−0.1111
	(0.0916)	(0.1050)
AQI_{t-3}	0.0089	−0.0119
	(0.0799)	(0.0854)
Weather	Yes	Yes
Holiday	Yes	Yes
Month FE	Yes	Yes
City FE	Yes	Yes
N	2370	2370

Robust standard errors are in the parentheses.
*** $p < .01$.
** $p < .05$.
* $p < .10$.

Table 9
The effect of air pollution on tourism development in destination cities with different levels of tourism resources.

	Visitors		Income	
	(1)	(2)	(3)	(4)
Panel A: TR < 5				
AQI	−0.1422	−1.3270***	−0.2085*	−1.1534**
	(0.1017)	(0.5030)	(0.1199)	(0.5330)
Weather	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	2142	2142	2142	2142
Panel B: 5 ≤TR < 7				
AQI	−0.6843	−1.0482***	−0.7798	−0.6166*
	(0.1390)	(0.3803)	(0.2031)	(0.3593)
Weather	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	81	81	81	81
Panel C: TR ≥7				
AQI	0.0493	0.9773	−0.4369*	−15.9731
	(0.1464)	(9.9921)	(0.1046)	(73.0153)
Weather	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	147	147	147	147

Robust standard errors are in the parentheses.
*** $p < .01$.
** $p < .05$.
* $p < .10$.

Heterogeneity of destination cities

Tourism resources

We select the total number of world heritage and national 5A level tourist attractions (TR) in a city as the proxies of the level of the city's tourism resources, and duplicate TRs are not removed. We obtain the number of world heritage sites from the website of the Chinese World Heritage and the website of the World Heritage. The number of national 5A level tourist attractions are acquired from the website of the Ministry of Culture and Tourism of the People's Republic of China. The results are summarized in Table 9. The OLS regression results are presented in Columns (1) and (3), while the IV regression results are presented in Columns (2) and (4). We find that the negative effect of air pollution is weakened when the number of tourism resources reaches a certain level. In other words, the attraction of tourism resources to tourists can partially offset the negative effect of air pollution on tourism development, reducing the losses of tourism economy caused by air pollution.

Infrastructure

We consider the total number of hotels in various cities. This number is derived from Ctrip, which is the most well-established travel agency in China. We use this metric as a proxy of the infrastructure level of tourism destinations. The estimation results are summarized in Table 10. Columns (1) and (3) present the results of OLS estimation, while Columns (2) and (4) report the results of IV estimation. We find that the impact of air pollution on tourism development in a city is not significant when its tourism infrastructure level is low. The reason for this may be as follows. Firstly, such a city may not be a famous tourist city, so air pollution has little impact on its number of tourists. Secondly, the tourism economy of such a city is still developing, so air pollution has little impact on the development of its tourism economy (measured by tourism income). However, with the development of infrastructure, tourism destinations will become more attractive to tourists, which can partially offset the losses to the tourism economy caused by air pollution.

Discussions and conclusion

Strengths of the research

Our study has several strengths. Firstly, our panel dataset covers very detailed and comprehensive tourism information, air quality and weather conditions about the 58 sample cities, e.g. tourist arrivals, tourism receipts, air quality (both AQI and $PM_{2.5}$), number of

Table 10
The effect of air pollution on tourism development in destination cities with different levels of infrastructure.

	Visitors		Income	
	(1)	(2)	(3)	(4)
Panel A: Hotel ≤ 500				
AQI	0.0193	−0.4329	0.0341	−0.3356
	(0.1604)	(0.5477)	(0.2105)	(0.6248)
Weather	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	836	836	836	836
Panel B: 500 < Hotel ≤ 4000				
AQI	−0.2695**	−2.8172**	−0.3983***	−2.5993**
	(0.1264)	(1.2839)	(0.1337)	(1.2686)
Weather	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	1261	1261	1261	1261
Panel C: Hotel > 4000				
AQI	−0.1424	−1.3709***	−0.2094	−1.1276***
	(0.1620)	(0.4586)	(0.1365)	(0.4303)
Weather	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	273	273	273	273

Robust standard errors are in the parentheses.
*** $p < .01$.
** $p < .05$.
* $p < .10$.

hotels, attractions, weather conditions, etc. Such information is collected from various highly credible data sources and spans between October 2013 to December 2017 on a monthly basis. We have made huge efforts to collect the information, match the data and compile the dataset. To the best of our knowledge, no prior research used such fine-grained data to study the relationship between air pollution and tourism development. Such high-quality dataset enables us to gain precise insights into the interplay between air pollution and tourism management. Secondly, we adopt a very rigorous empirical strategy. We select wind speed, an exogenous meteorological condition which is independent of economic activities, as an instrumental variable to effectively handle the endogeneity caused by the interplay between air pollution and tourism development. Such an IV approach enables us to well catch the interplay, which has never been examined in prior literature. Thirdly, we conduct a series of analyses to test the effects of potential threats, time (i.e. the intertemporal effects) and heterogeneity of destination cities on the interplay between air pollution and tourism development. These analyses show that our results are very robust. We thus make a significant empirical contribution.

Policy implications

We derive interesting empirical evidence which offers significant policy implications for policy makers. First of all, our empirically confirm that air pollution can negatively affect tourism development, and such effect holds under endogeneity controls and in robustness checks. This means that if a city/region would like to develop a tourism economy, it should pay much attention to the quality of its air. This can be achieved through relevant legislation to regulate economic activities such as traffic, construction, manufacturing, residential energy consumption, etc. which can cause air pollution. The UK Clean Air Act 1956 and the US Clean Air Act of 1963 provide good international experience for China. We can see that in recent years some cities in China made progress in air cleaning. Beijing made the Clean Air Action Plan 2013–2017, and it resulted in significant reductions in $PM_{2.5}$, PM_{10}, NO_2, SO_2, etc. (Vu et al., 2019). In the long run, more cities should develop similar local policies to regulate their relevant economic activities, which can lead to clean air and tourism economy prosperity. Secondly, we empirically find the interplay between air pollution and tourism development. Tourism development can cause air pollution, and when air pollution is noticeable, it can influence tourism development. Therefore, there is an optimum point for the combination of air quality and tourism. Properly utilizing such optimum point can enable resources for tourism development be used most efficiently. Thirdly, we empirically find that tourism resources and hospitality infrastructure can weaken the negative effect of air pollution on tourism development. Therefore, for cities that would like to develop tourism economies, developing famous attractions and establishing mature hospitality infrastructure are essential, even if these cities has air pollution. One example is Xi'an, located in northwest China and famous for the Terracotta Army. This city has air problems for long (so do many other cities in northwest China). Well-established hospitality infrastructure can partially offset the negative effect of air problems, thus contributing to its tourism economy development. Fourthly, we empirically show that air pollution in one month can continuously affect tourism development for two consecutive months. Therefore, air pollution has continuous negative effect on tourism development. It is important to give frequent real time updates of air quality to tourists, so we may be able to minimize the time-lagged negative effect of air pollution to tourism development.

Limitations and future research

We, of course, should acknowledge the limitations of our study. First, when we examine the heterogeneity of destination cities, we do not consider traffic which is a very important part of city infrastructure. Traffic can influence both air quality and tourism development in the destination cities. Thus, it presents a very interesting and complex effect on the interplay between air pollution and tourism development. Second, we do not consider the profiles of the tourists to the destination cities. Different types of tourists have different views on air pollution. Thus, their profiles can influence the interplay. Third, our study is based in China. We do not presumptuously claim that our empirical findings are applicable in other countries. The external validity needs to be tested. Future research can address these issues if relevant data can be derived.

CRediT authorship contribution statement

1. What is the contribution to knowledge, theory, policy or practice offered by the paper?

This paper empirically examines the interplay between air pollution and tourism development, a topic that has not been effectively addressed in prior tourism literature. We conducted a comprehensive literature review to understand the state-of-the-art of the research on the relationship between air pollution and tourism development. Based on a fine-grained dataset covering high-resolution information about tourism, air pollution, weather conditions, etc. of 58 major cities in China, we adopted a sophisticated empirical strategy and gained empirical evidence of the interplay, which significantly advances our knowledge of the interactive relationship between air pollution and tourism development. Our empirical findings offer important policy implications for developing a sustainable tourism economy in China.

2. How does the paper offer a social science perspective/approach?

Both air pollution and tourism development are significant social issues that trigger strong social attention. Therefore, this paper has been well positioned in social science. Additionally, the paper offers three important methodological implications in social science. Firstly, many causalities in social science domains are bi-directional (e.g. the relationship between air pollution and tourism development in our research). Examining the relationships between social constructs/variables uni-directionally may generate insights that are less effective for social policy making. It is important to look at the interplays between social constructs/variables. Secondly, compiling a high-quality dataset covering high-resolution information from various sources is important in future social science research, as this approach can effectively overcome the limitations of prior research. Thirdly, using exogenous variables (e.g. wind speed in our research) as instrumental variables in the empirical strategy can effectively handle the endogeneity caused by the reverse causalities between social constructs/variables.

Declaration of competing interest

None.

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