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Exploring the effect of air pollution on social activity in China using geotagged social media check-in data

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ABSTRACT

Understanding the complex impact of air pollution is crucial to assessing exposure risk and defining public health policies in China. However, the evidence and hence knowledge of how urban activity responds to air pollution are limited. In this paper, we propose to use geotagged check-in records on Weibo, a Tweeter-like platform, to systematically investigate the effect of air pollution on urban activity.

Based on panel models, we found clear evidence that such effect exists and varies between pollutants, visitors and residents, and different activity types. Typically, SO_2 has the largest impact, followed by $PM_{2.5}$, NO_2, and PM_{10}; local citizens' activities are more susceptible than visitors; leisure-related activity has a sensitivity at least twofold higher than work-related activities. Additionally, we tested hypotheses about the heterogeneous effect. We confirmed the role of *Income* and air quality, showing that people who live in richer and more polluted cities are more likely to experience the effects of air pollution. Specifically, people who live in a more polluted city with 100 unit increments in *AvgAQI* show on average the same sensitivity as those who live in a less polluted city and earn about 20.3 thousand yuan more in average *Income*.

This reveals new insights about environmental injustice in China. By presenting a portrait of the spatial heterogeneity, we argued that environmental injustice in terms of air pollution is not just about the difference in exposure risk measured based on population distribution, rather the measurement should also consider the disparity derived from urban activity. Secondly, new injustice may arise in underdeveloped areas where manufacture industry is transferred to but people barely take avoidance behavior. Finally, the map also reveals the general neglect of the detrimental effect of light air pollution, which we speculate is partly due to China's comparatively low standard in governmental regulations.

We believe our finding contributes significantly to exposure risk assessment and environmental justice debates. Hence it highlights the necessity and urgency of public healthy polices that spread the health consequence of air pollution, especially in the underdeveloped region.

1. Introduction

Air pollution in China has been causing severe health consequences. Research demonstrates that air pollution in China may have caused health-related economic losses of 1.63% to 2.32% of the GDP (Li, Lei, Pan, Chen, & Si, 2016), and is calculated to contribute to 1.6 million deaths per year — roughly 17% of yearly deaths in China (Rohde & Muller, 2015). In North China, the most affected area (Li & Sun, 2018), long-term exposure to total suspended particulates may have reduced life expectancies by about 5.5 years (Chen, Ebenstein, Greenstone, & Li, 2013). In fact, China has been one of the countries with the highest particulate matter levels in the world (Chen et al., 2013). Air pollution in most Chinese cities exceeds 6 to 20 times the values suggested by the World Health Organization Air Quality Guidelines (Chan & Yao, 2008; Long, Wang, Wu, & Zhang, 2014). Meanwhile, both the recent industrialization and urbanization of China are aggravating the problem (Sheng & Tang, 2016; Zheng & Kahn, 2013).

The same challenge lies in the potential adverse impact of air pollution on urban activity. People come to cities to benefit from the social interactions facilitated by high urban density, a process known as urbanization. Air pollution, however, is a kind of friction that impedes such interactions, and thus reduces the value of urban density. Air

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pollution may lead directly to health consequences and then further change urban activity patterns and finally cause a systematic influence on urban interactions. Researchers have found clear evidence that air pollution may cause a decline in activity frequency and life satisfaction (MacKerron & Mourato, 2009). Taking a long-term view of the coming urban era, such adverse effect could bring not only a slowdown to urbanization in developing areas but also bring about a decline of the urban economy in developed regions. For instance, a study in Los Angeles estimated that avoidance behavior due to ozone causes $11 million of losses per year, about 25% of the annual costs from respiratory-related hospitalizations (Moretti & Neidell, 2011).

From the short-term view, understanding the effect of air pollution on urban activity is also crucial in terms of reducing and assessing the exposure risk. The theoretical base is that a rational individual may cancel or postpone discretionary activities when heavy pollution happens, resulting in an overestimate of their exposure risk. In contrast, the exposure risk of those who have more indispensable activities may be comparatively underestimated. However, current studies failed to present an accurate portrait of which population groups are more affected by air pollution because such studies often measured exposure based on home locations (e.g., Long et al., 2014; Mitchell & Dorling, 2003). In fact, several studies have revealed significant discrepancies between pollutant concentrations at home location and the overall personal exposure to pollutants (Avery et al., 2010; Nyhan, Mcnabola, & Misstear, 2014), with causal factors including daily movement patterns, varying activities throughout the day, and microenvironments (Dons et al., 2011; Kaur & Nieuwenhuijsen, 2009; Nieuwenhuijsen et al., 2015; Schembari et al., 2013; Valero et al., 2009). Recently, some studies have pioneered the use of cellphone data (Nyhan et al., 2016) or simulated individuals' mobility patterns (Burke, Zufall, & Ozkaynak, 2001) to provide a better exposure evaluation by taking into consideration daily mobility patterns. Obviously, direct measurement of the effect is still needed to evaluate to which extent the exposure risk is biased.

In spite of the importance, evidence of the relationship between air pollution and urban activity is far from enough. Only a few empirical analyses have been conducted, showing that avoidance behavior may only exist under certain circumstances. For instance, studying children's hospital emergency admissions data from England, Janke (2014) found evidence of avoidance behavior in response to air pollution warnings but only when such behavior costs little. Based on time use diaries, Bäck, Kuminoff, Buren, and Buren (2013) confirmed that conditional on weather, only children and older adults reduced outdoor leisure when pollution reached very unhealthy levels. Using the attendance records of two outdoor facilities, Zivin and Neidell (2009) found that avoidance behavior exists on the first day of a smog alert but decreases when alerts are issued on two successive days. Since urban activity is not well represented in these studies, it is still a question that whether the adverse effect of air pollution on urban activity is marginal or not.

Additionally, studies related to environmental injustice also shed light on the potential association between air pollution and urban activity. In Western cases, researchers (Boone, Fragkias, Buckley, & Grove, 2014; Jerrett et al., 2001) showed that people with lower socioeconomic status are exposed to higher levels of air pollution. And studies suggest that there are serious environmental inequalities associated with income level (Bevc, Marshall, & Picou, 2007; Krieg & Faber, 2004), with the poor being exposed to environmental pollution more than the middle class. Similarly, Mitchell and Dorling (2003) found that in Britain those with the least ability to move away from poor air quality (children and the poor) do indeed suffer the greatest exposure. Another indirect evidence comes from Ferreira and Moro (2013), who hypothesized that richer people are better able to substitute social activities by undertaking costly averting actions. In China, however, the conclusion seems to be inconsistent. Researchers found that people living in prefectures with higher income levels are also more likely to bear a higher industrial environmental burden (He, Fang, Ji, & Fang, 2017) and the poor do not suffer more from environmental pollution than the rich (Ma, 2010), while another study shows that richer people are more likely to invest in masks and air filters to protect themselves from pollution (Sun, Kahn, & Zheng, 2017). Apparently, understanding how urban activity responds to air pollution may contribute significantly to a better environmental injustice evaluation.

We now summarize three important questions that still remained to be answered. Firstly, do people in developing countries, such as China, demonstrate the same avoidance behaviors at the same rate as in developed countries? The answer will be important for understanding the social costs of air pollution in different economies. Secondly, if air pollution has a significant impact on urban activity, then to what extent does it affect urban activity and how the impact changes with factors such as population groups, activity types, and socioeconomic status? This paper uses open data, and as a result we provide answers from a large-scale evaluation and a detailed heterogeneity analysis along several dimensions. Thirdly, in addition to the questions above, what can these new findings add to the global social debate over the impact of air pollution, particularly in terms of environmental injustice and related urban development policies?

To address these questions, we organize this paper as follows. In the data section, we present a detailed description of the datasets we use. All the pre-processing procedures and representativeness tests are carefully explained to endorse the effectiveness of the result. In the method section, we describe the three panel regression models used in this paper as well as all the involved variables. In the results and discussion section, we first present the evidence and measurement of the general effect of air pollution on urban activity. Then both the statistical test result of the interactive factors and the spatial heterogeneity are presented, based on which several new aspects of China's environmental injustice are thoroughly discussed.

2. Data

2.1. The geo-tagged Weibo check-in activity in China

2.1.1. Data source and pre-process

We use social media check-in data on Sina Weibo as a proxy for human social activity records. The Sina Weibo micro-blogging platform, the Chinese answer to Twitter, is one of the biggest social networking services in China with about 300 million active monthly users in 2016 when we collected our data. For the specific dataset we use, the total check-in records correlate well with urban population and GDP in logarithmic form with coefficients as high as 0.73 and 0.77 respectively. Both the widespread use and the statistics endorse the representativeness of Weibo data, demonstrating that the continuous records provide an effective portrait of social activity dynamics. Furthermore, as a kind of volunteered geographic information (VGI), it contains exact locational and functional information about activities and that cannot be gathered from passive LBS data. In fact, it has been widely used in human mobility and urban structure analyses (e.g., Liu & Wang, 2016; Wu, Zhi, Sui, & Liu, 2014) and even air pollution trends detection (Jiang, Wang, Tsou, & Fu, 2015; Jiang, Wang, Tsou, & Fu, 2016; Mei, Li, Fan, Zhu, & Dyer, 2014; Shi & Gao, 2017; Wang, Jing, Jiang, Wang, & Xiaokang, 2017).

We based our analysis on check-in records attached with a POI (point of interest), but we abandon the POIs with less than twenty accumulated check-ins to reduce workload. As a result, we captured the check-in records at 1.1 million POIs from January 1st, 2015 to October 30th, 2016. Our final dataset consists of 50 million geotagged check-in records across China, from about 640,000 unique users. We identified the home city of each user by extracting the most frequent city in which the user appears. Then check-ins in the home city were aggregated into the local citizens' activity, in contrast to visitors' activity.

We consider the dataset as a virtual representation of urban activity. To test that, we extracted the "urban area" by population density larger than 1500 per km^2 according to Chinese regulation,[1] considering that there is no absolute distinction between suburban and rural. The result shows that about 87.8% of the POIs and 90.9% of the check-in records are located in urban area. Moreover, urban and rural areas are closely integrated in terms of social activity. Eliminating check-ins outside urban areas may lead to a biased measurement of the impact of air pollution on many types of activities such as hiking, picnicking, and sightseeing in the surrounding rural area. Thus we don't separate the check-ins by areas.

Furthermore, it should be noticed that we did not differentiate between indoor and outdoor activity. Although in many places check-ins could be roughly labeled as indoor or outdoor, e.g., museums versus parks, most urban activities other than residence require travel through the outdoor environment. Therefore, check-ins at residential POIs are ignored when counting numbers, beyond which no more indoor/outdoor labels are needed.

2.1.2. Activity categories

The basic role of social media in our life is to share information with friends. Although there is no guarantee that everyone has to attach the right position, most of the time sharing an activity with the exact POI is what we need. Thus defining activity types based on the tagged POI is reasonable. The original POIs are divided by the Weibo platform into > 200 types, such as cafés, cupcake shops, and seafood restaurants. In this paper, to reveal the effect of air pollution on different kinds of urban activity, we merge the original types into 7 activity categories (Table 1) according to land use regulations, and of these we are particularly interested in the difference between work-related activities and leisure-related activities. Also note that people may conduct work-related activities in a leisure-related place as a freelancer or an employee, however, we still believe that the POI categories generally provide rich information about the urban activity types that other open data sources cannot offer on such a large scale. (See Table 2.)

It is important to notice that statistics according to the categories reveal potential biases of the check-in data. Comparing with the fifth travel survey analysis (2011), in which about 40% of the travel activities are commuting, here in our data the work-related activity has a proportion of 5.84% plus 8.90%, while the public service and leisure-related activity become the commonest ones. We acknowledge that there is an over-representation of public service, leisure-related, and tourism activity, and an under-representation of work-related and public transportation activity. However, it is well known in transportation studies that commuting activities usually dismiss the short pedestrian trips to and from mass transit, or from parking garages to the final destination. Thus, although we recognize the biases, Weibo POI still reveal a granularity seldom seem in urban analysis. Future studies on biases on social media must be done in future works.

2.2. Ground-based air pollution observations

2.2.1. Data source

Air pollution data consists of the daily 24-hour averaged concentration records of the so-called criteria air pollutants and one indicator (AQI, air quality index) for every prefecture city released by the Ministry of Environmental Protection of China during the same period. The six pollutants are $PM_{2.5}$ (particulate matter < 2.5 μm), PM_{10} (particulate matter < 10 μm), SO_2 (sulfur dioxide), NO_2 (nitrogen dioxide), CO (carbon monoxide) and O_3 (ozone). The measurement units of the pollutants are set to $\mu g/m^3$ (microgram per cubic meter). The weather records, including precipitation, temperature and wind force, are provided by China Meteorological Data Service Center.

[1] http://www.stats.gov.cn/tjsj/pcsj/rkpc/5rp/html/append7.htm

2.2.2. Multi-collinearity

Since pollutants may come from the same sources (e.g., industries, traffic, and other combustion sources), it is not surprising that these air pollutants are temporally correlated. For example, the correlation coefficient between $PM_{2.5}$ and the PM_{10} could be as high as 0.8. Since every pollutant may indicate inherently unique causes and effects on human health and urban activity, we retain all of them in this study and put each of them into the model separately to avoid collinearity. Moreover, in the heterogeneous effect sections we only present the result of AQI, since the test results of different pollutants are generally similar.

2.3. Data integration

After removing cities and days with missing records for air pollution, weather condition or geo-tagged check-ins, the final dataset used in this article comprises 630 days and 251 prefecture cities. According to the official definition of city size in China,[2] our sample includes every city size, from small cities to super mega-cities, and covers most of the populated regions, as shown in Fig. 1.

The average daily check-in number is 294, with about 40 check-ins per user per year. Fig. 2 shows the average daily check-ins in quantile, which illustrates that the most populated as well as developed cities, including the coastal cities in the east, the south, and the capitals of the central and west provinces, form the first quantile with average daily check-in numbers larger than 283.

Fig. 3 shows the distribution of the average pollution level of each pollutant in China. All maps show the same pattern: North China has the worst air quality, and the Yangtze Delta Region and some other part of the east coast region (e.g., Shandong province) also suffer heavily from some air pollutants. Central and South China have relatively better air quality when viewed from the averaged values.

2.4. Other factors

2.4.1. Weekends & holidays

Urban activities are highly influenced by weekends and holidays. This pattern is also seen in Weibo check-ins activity, which increases dramatically on weekends and holidays. To control for this effect, we added two dummy variables in the models representing whether a day is a weekend or national holiday.

2.4.2. Seasons & weather

Seasonal and weather conditions also affect urban activity. To control for seasonal variation, we divide all dates into four seasons based on the Chinese lunar calendar. We also control for daily precipitation capacity as a representative of weather conditions.

3. Methods

3.1.1. Panel regression

Our final sample consists of 630 days and 251 prefecture cities, forming a strongly balanced panel dataset. Then, we implemented the Fixed Effects Model (FEM), the most commonly used panel regression method, to reveal the potential effects of air pollutants on urban activity. The expression is

$$y_{it}^{activity} = \beta_1 X_{it}^{pollution} + \beta_2 X_{it}^{weather} + \beta_3 X_{it}^{date} + u_i + \varepsilon_{it} \quad (1)$$

[2] In China, the cities are classified into six classes by population size: Super mega-cities (> 10,000,000), Mega-cities (5,000,000-10,000,000), Big cities (1,000,000–5,000,000), Medium-sized cities (500,000–1000,000), Small cities class one (200,000–500,000), Small cities class two (< 200,000).

Table 1
Aggregation from original POI types to activity categories.

Activity categories	Original POI types	Activity proportion
Work-related	Companies, office building, factory, etc.	5.84%
Public transportation	Stations, bus stop, subway station, airport, harbor, etc.	8.90%
Residence	Community names, apartments, residential quarter, etc.	11.53%
Public service	School, hospital, police office, government administration, etc.	25.34%
General place	General landmarks such as cities, towns, addresses, etc.	6.27%
Leisure-related	Market, restaurant, gyms, bar, museum, art gallery, etc.	26.73%
Tourism	Hotel, temple, scenic spot, famous location, etc.	14.94%

Table 2
Variable definitions and summary statistics.

Variables	Definition	Obs.	Mean	Std.
Activities	Daily total check-in numbers in each city, divided into two groups (local citizens and visitors) or divided into six detail activity types.	158,130	293.80	910.97
Source: Sina Weibo platform, https://weibo.com/				
AQI	Daily air quality index	158,130	80.31	44.22
$PM_{2.5}$	24 h average concentration of $PM_{2.5}$ (μg/m^3)	158,130	48.20	37.41
PM_{10}	24 h average concentration of PM_{10} (μg/m^3)	158,130	82.84	57.55
NO_2	24 h average concentration of NO_2 (μg/m^3)	158,130	30.77	16.79
SO_2	24 h average concentration of SO_2 (μg/m^3)	158,130	23.99	23.77
CO	24 h average concentration of CO (μg/m^3)	158,130	1065.43	601.10
O_3	24 h average concentration of O_3 (μg/m^3)	158,130	90.21	43.00
AvgAQI	Average daily AQI in each city across	251	80.31	19.79
Source: Ministry of Environmental Protection of China				
Temp	Daily average temperature (°C)	158,130	21.6	10.2
Wind	Daily average wind scale (level)	158,130	3.21	0.50
Rain	Daily precipitation capacity (mm)	158,130	3.70	9.82
Source: China Meteorological Data Service Center				
Holiday	Dummy: 1 = national holiday, 0 = otherwise	630	0.08	0.50
Weekend	Dummy: 1 = Saturday or Sunday, 0 = otherwise	630	0.23	0.42
Season	Dummy: 4 seasons represented by 3 dimensional vectors according to lunar calendar	630	0.56	0.50
UrbanPop	Urban population of each city in 2014 (10,000)	251	459	292
Income	Average annual income per worker (10,000 RMB/year) of each city in 2014	251	3.18	0.76
Source: China City Statistical Yearbook 2015				

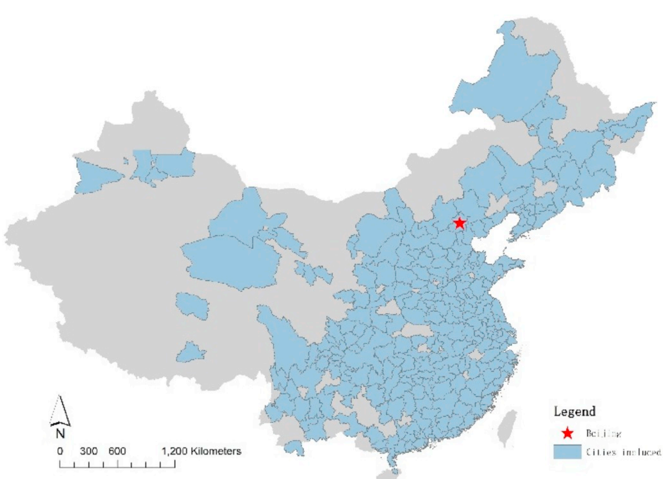

Fig. 1. The sampled 251 prefecture cities.

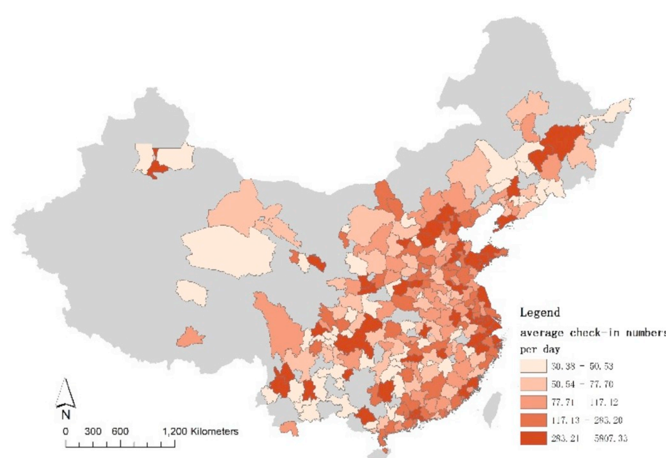

Fig. 2. The daily check-in number in each city.

The dependent variable $y_{it}^{activity}$ could be the total activity number or the amount of any specific activity type at city i on day t. $X_{it}^{pollution}$ is one of the six air pollutants' concentration levels at city i on day t. We expect the pollution coefficient (β_1) will be negative. $X_{it}^{weather}$ is a vector consisting of *Temp* (temperature), *Wind* (wind scale), and *Rain* (precipitation capacity). X_{it}^{date} is also a vector comprised of *Weekend*, *Holiday* and *Season*. u_i is the fixed effect on each city, which varies because of differences in population, economic development, living habit and even popularity of Weibo, and ε_{it} is the error term.

Meanwhile, interaction terms (X_{it}^{inter}) are added into the augmented Eq. (2) to investigate the heterogeneity of the effect. The method is utilized to test general heterogeneity of the effect regarding income, average air quality, holiday, season, or to verify the spatial heterogeneity of the effect based on the regional division obtained by the following varying coefficient models.

$$y_{it}^{activity} = \beta_1 X_{it}^{pollution} + \beta_4 X_{it}^{inter} X_{it}^{pollution} + \beta_2 X_{it}^{weather} + \beta_3 X_{it}^{date} + u_i + \varepsilon_{it} \quad (2)$$

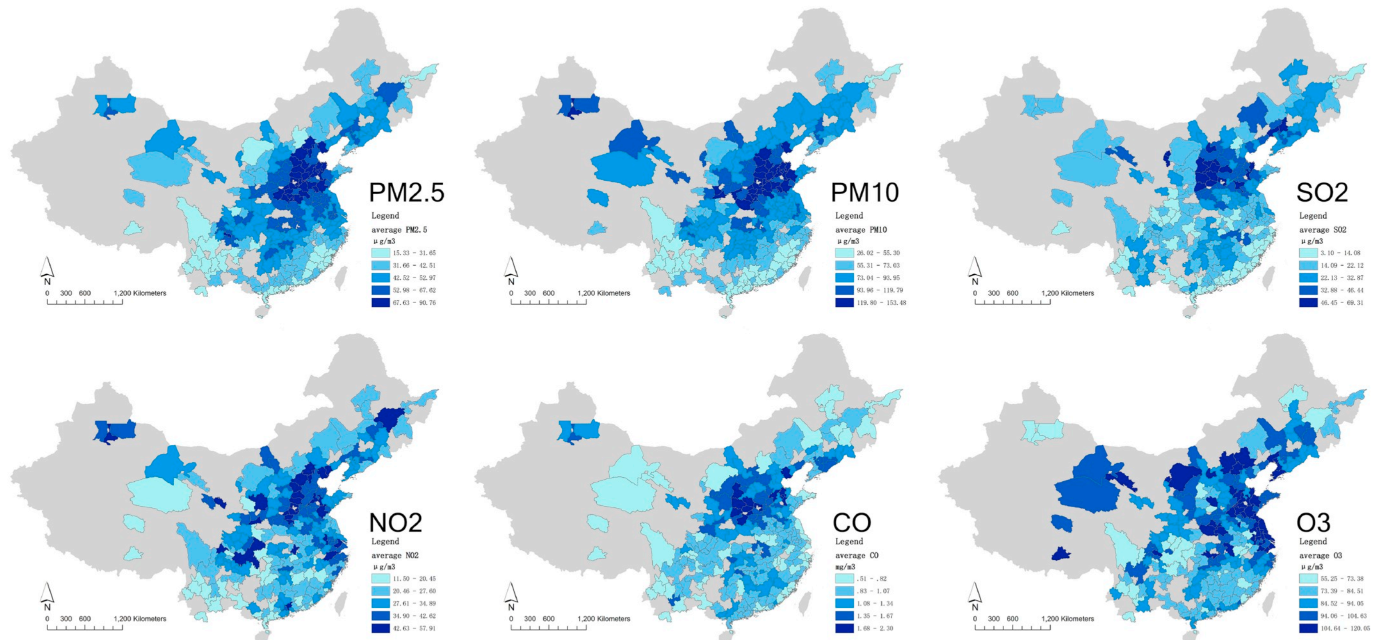

Fig. 3. Average pollution concentration across the cities, classified and colored into five groups by Jenks Natural Breaks.

3.1.2. Varying coefficient model

It is naturally right and axiomatic to postulate that citizens should have the same sensitivities to air pollution. However, due to possible cultural, psychological and even historical reasons, there could be spatial variation of the effects of pollution across the cities. In fact, all the chi-square tests in the FEMs result in significant rejection of the parameter constancy hypothesis, i.e., all the cities have the same β_1. To locate the heterogeneous effect spatially, and to detect potential heterogeneity caused by other implicit factors, we change the model form to a varying coefficient model, as in Eq. (3), which lets each city have a specified β_{1i} and keeps the other terms the same as in Eq. (1).

$$y_{it}^{activity} = \beta_{1i}X_{it}^{pollution} + \beta_2 X_{it}^{weather} + \beta_3 X_{it}^{date} + u_i + \varepsilon_{it} \quad (3)$$

4. Results and discussion

4.1. General effect of air pollution on urban activity, regarding different air pollutants, people, activity types, and air quality alert levels

4.1.1. General adverse impact of different air pollutants

In contrast to the conditional evidence in the literature, here we find clear proof that avoidance behavior exists, i.e., air pollution causes a general and significant decline in total urban activity. In Tables 3 and 4, each row exhibits the coefficients of one air pollutant when put into the model respectively, with the other factors controlled as described in eq. (1). The result shows that avoidance behavior generally exists with respect to $PM_{2.5}$, NO_2, SO_2, and PM_{10}. Specifically, an increase of 100 μg/m^3 of the four pollutants will lead to an average decrease of 8.4–27.6% in the total local activities. That is a huge decline even for one day, not to mention the accumulative loss in many cities where severe pollution happens frequently. Taking $PM_{2.5}$ as an example, in the study period the total accumulative loss of the local activities across the country is estimated to be as large as 6.7%. If multiplied by the total urban social consumption in 2015, at some risk of oversimplifying, the annual monetary loss will be up to 1.7 trillion RMB yuan (about 260 billion dollars)!

Huge differences exist among air pollutants in terms of how they affect urban activity. CO and O_3 seem not always significantly relevant to the urban activity, although their coefficients are always negative. We speculate that the disparity between pollutants is partly due to perceptual differences, which may further relate to their chemical properties, such as smell (Cole, Pengelly, Eyles, Stieb, & Hustler, 1999).

4.1.2. Local citizens and visitors

Surprisingly, the impact differs dramatically between local citizens and visitors. As shown in Tables 3 and 4, every 100 μg/m^3 increments in the concentration of the first four air pollutants ($PM_{2.5}$, PM_{10}, NO_2 and SO_2) causes an average 19–61 decrease in local citizens' activities, at least 4 times the effect observed for visitors' activity, which shows only a 4–8 decrease. For local residents, SO_2 has about 50% more effect on urban activity than the second pollutant ($PM_{2.5}$), followed by NO_2 and PM_{10} with close coefficients. However, for visitors' activity, although the rank remains the same, both the effect and the differences between pollutants' coefficients are not that striking. Furthermore, this difference between local citizens and visitors is consistent across every activity. This finding supports the conclusion that air quality is only a minor concern to tourists (Cheung & Law, 2001). Likely this could be explained by the fact that traveling expense is a sunk cost and the limited duration of the visitors' travel, which makes it less cost-effective to rearrange their activities than it is for local residents.

4.1.3. Different types of activity

It is also evident that leisure-related activities are more susceptible to air pollution than work-related activities. For local residents, the effect on leisure-related activities represented by the coefficients is about 4–6 times higher than for work-related activities, while for visitors this difference is reduced to 2–4 times. This phenomenon corresponds perfectly with some of the empirical evidence above (Bäck et al., 2013; Graff Zivin & Neidell, 2009), which however didn't provide a comparison between leisure with other activity. With such a huge difference measured here, we propose that this observation can be explained by more general theories such as in time-geographic studies, which argue that different activity patterns of work and leisure are mainly due to spatial-temporal fixity (Schwanen & Kwan, 2008).

In further analyses, we verified this differential across the six activity types. According to Tables 3 and 4, if we sort the activity categories from the most susceptible to the least, i.e., from the smallest negative coefficients to the largest, it would be: *Entertainment* > *Public Service* > *Tourism* > *Work Place* > *Public Transport* ≈ *General Place*.

Table 3
The general effect of air pollutants on each type of local citizens' activity.

Variables	Total activities	Leisure-related	Public service	Tourism	Work-related	Public transport	General place
AQI	−0.203***	−0.093***	−0.046***	−0.029***	−0.015***	−0.008***	−0.011***
	(0.034)	(0.015)	(0.010)	(0.004)	(0.003)	(0.002)	(0.002)
$PM_{2.5}$	−0.329***	−0.144***	−0.080***	−0.044***	−0.026***	−0.013***	−0.020***
	(0.041)	(0.018)	(0.012)	(0.005)	(0.004)	(0.003)	(0.002)
PM_{10}	−0.187***	−0.082***	−0.042***	−0.023***	−0.017***	−0.010***	−0.010***
	(0.027)	(0.012)	(0.008)	(0.003)	(0.002)	(0.002)	(0.001)
NO_2	−0.261**	−0.166***	0.040	−0.053***	−0.030***	−0.032***	−0.012**
	(0.103)	(0.046)	(0.030)	(0.013)	(0.009)	(0.006)	(0.005)
SO_2	−0.612***	−0.228***	−0.214***	−0.066***	−0.052***	−0.021***	−0.024***
	(0.071)	(0.031)	(0.021)	(0.009)	(0.007)	(0.004)	(0.004)
CO	−3.936	−1.192	−1.328	−0.900**	−0.254	−0.161	−0.084
	(2.780)	(1.241)	(0.834)	(0.357)	(0.255)	(0.174)	(0.145)
O_3	−0.027	−0.029	0.009	−0.005	−0.006*	−0.0006	0.003
	(0.040)	(0.018)	(0.012)	(0.005)	(0.004)	(0.003)	(0.002)

Note: Each grid refers to a model that evaluates the effect of one air pollutant on one activity type based on Eq. (1); * $p < 0.1$, ** $p < 0.05$, ** $p < 0.01$; The adjusted R^2 are stable at 0.45.

Table 4
The general effect of air pollutants on each type of visitors' activity.

Variables	Total activities	Leisure-related	Public service	Tourism	Work-related	Public transport	General place
AQI	−0.032***	−0.006***	−0.002**	−0.009***	−0.002***	−0.010***	−0.002***
	(0.006)	(0.002)	(0.001)	(0.002)	(0.0004)	(0.001)	(0.0004)
$PM_{2.5}$	−0.059***	−0.014***	−0.008***	−0.015***	−0.004***	−0.013***	−0.004***
	(0.007)	(0.003)	(0.002)	(0.002)	(0.0005)	(0.001)	(0.0005)
PM_{10}	−0.035***	−0.009***	−0.005***	−0.007***	−0.002***	−0.009***	−0.002***
	(0.005)	(0.002)	(0.001)	(0.001)	(0.0003)	(0.0008)	(0.0003)
NO_2	−0.062***	−0.027***	0.002	0.001	−0.006***	−0.027***	−0.004**
	(0.018)	(0.007)	(0.004)	(0.005)	(0.001)	(0.003)	(0.001)
SO_2	−0.075***	−0.006	−0.020***	−0.021***	−0.004***	−0.019***	−0.004***
	(0.012)	(0.005)	(0.003)	(0.003)	(0.001)	(0.002)	(0.0009)
CO	−1.001**	0.359*	−0.180	−0.473***	−0.039	−0.521***	−0.130***
	(0.480)	(0.195)	(0.111)	(0.134)	(0.034)	(0.087)	(0.034)
O_3	−0.017**	0.003	0.011***	0.0007	0.002***	−0.002*	0.004***
	(0.007)	(0.003)	(0.002)	(0.002)	(0.0005)	(0.001)	(0.0004)

Note: Each grid refers to a model that evaluates the effect of one air pollutant on one activity type based on Eq. (1); * $p < 0.1$, ** $p < 0.05$, ** $p < 0.01$; The adjusted R^2 are quite stable at 0.71.

(Note that for visitors this sequence may change slightly). Although we didn't measure the fixity of each type of activity, based on the result and the theories, we believe it is reasonable to assume that activities with higher spatial-temporal flexibility can be more easily re-arranged or canceled to reduce exposure risk, which leaves the more fixed activities, such as work and public transportation, to be more affected by air pollution.

4.1.4. Time lag effect

A time lag effect may exist that on a polluted day people may cancel future activities which last for several days. In our test, for a time lag of < 10 days, the lagged AQI item is always significant with $P < 0.01$. However, this is probably just caused by autocorrelation of the pollution on continuous days. Unfortunately, this paper cannot provide further evidence for this. We expect further studies could explain this with better research design.

4.2. Heterogeneity of the effect

4.2.1. General heterogeneity of the effect

The current literature has provided fragmentary evidence of the heterogeneous impact of air pollution on urban activity. Two basic factors have been revealed: income and pollution level. As discussed in the introduction, people with lower socioeconomic status suffer from less flexibility in social choices such as residence relocation, urban activity substitution, and healthy investment. Similarly, people barely change activities in light-pollution weather. All in all, several detailed hypotheses are tested here. Since different cities have heavy concentrations of different pollutants, we report the result of the AQI as a representative of all the pollutants in Tables 5 and 6, considering it is calculated by the primary pollution.[3]

The first question is whether there exists a heterogeneous impact respectively and simultaneously caused by income and pollution level. Our answer is yes. As shown in columns (1) and (2), people in richer cities (with higher average income) and more polluted cities (with smaller *AvgAQI*) are significantly more susceptible to air pollution. Particularly, in a more polluted city with 10 unit increments in *AvgAQI*, the sensitivity of urban activity to air pollution increases by 14.65%, that is an additional 9 activities will be canceled on a specific day with an AQI of 100. Likewise, in a richer city with 10 thousand yuan more of average *Income*, sensitivity to air pollution increases by 38.3%. Put together in column (3), people who live in a more polluted city, with 100 unit increments in *AvgAQI* show on average the same sensitivity as those who live in a less polluted city and earn about 20.3 thousand yuan more in average *Income*. The result enhances the arguments that, for example, averting behaviors become more common when pollution levels exceed thresholds or the subjects are richer (Sun et al., 2017), and rich people substitute urban activity to reduce exposure and ensure

[3] Ministry of Environmental Protection (China), Technical Regulation on Ambient Air Quality Index, 2012.

Table 5
Test of the factors of general heterogeneity.

Variables	Total activities												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
AQI	1.061***	0.641***	2.056**	3.438**	−0.276***	0.210***	0.198***	−0.247***	−0.240***	−0.287***	0.061	−0.436***	4.832***
	(0.146)	(0.481)	(0.233)	(0.474)	(0.039)	(0.054)	(0.048)	(0.042)	(0.038)	(0.059)	(0.218)	(0.078)	(0.494)
AQI* Income	−0.406***		−0.418**	−1.150***									−2.754***
	(0.044)		(0.002)	(0.223)									(0.251)
AQI* AvgAQI		−0.009***	−0.010**	−0.010***									−0.002***
		(0.032)	(0.044)	(0.002)									(0.0002)
AQI* Income^2				0.094***									0.449***
				(0.027)									(0.036)
AQI* AvgAQI^2				0.001									
				(0.000)									
AQI* Holiday					0.309***								0.297***
					(0.104)								(0.104)
AQI* UrbanPop						−0.002***							0.0002
						(0.0001)							(0.0003)
AQI* GDP							2.219***						−5.509***
							(0.154)						(0.447)
AQI* Weekend								0.015					
								(0.076)					
AQI* Rain									−0.001				
									(0.003)				
AQI* Temp										−0.003			
										(0.003)			
AQI* Wind											−0.094		
											(0.067)		
AQI* Spring												0	
												(omitted)	
AQI* Summer												−0.046	
												(0.113)	
AQI* Autumn												0.526***	
												(0.108)	
AQI* Winter												0.179*	
												(0.090)	
Adj-R^2	0.5240	0.5242	0.5241	0.5242	0.5238	0.5242	0.5239	0.5241	0.5238	0.5241	0.5242	0.5243	0.5251

Note: * $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$.

Table 6
Statistics about air quality and exposure risk in six regions.

Index	Region	City number	Average yearly income (yuan)	Excellent city*days $PM_{2.5} < 12$	Excellent city*days $PM_{2.5} < 35$	Proportional exposure risk by population	Proportional exposure risk by activity
1	East China	40	37,081	1.53%	32.23%	33.77%	26.38%
2	North China	29	34,862	0.96%	25.67%	31.96%	37.98%
3	Northeast China	23	30,968	3.17%	38.14%	37.09%	41.22%
4	Middle China	40	28,148	3.30%	49.75%	23.20%	26.10%
5	Broader South China	99	27,049	5.48%	55.93%	11.65%	15.97%
6	Northwest China	20	27,865	2.07%	47.90%	26.06%	29.23%

Note: proportional exposure risk is calculated by the product of population/activity and the days with AQI larger than 100 divided by the total products of population/activity and days, in which 100 is the threshold of "pollution" according to the official regulation.

life satisfaction is not reduced (Ferreira & Moro, 2013). As far as we know, this is the first countrywide evidence that focuses directly on urban activities and confirms the heterogeneous effect of income and pollution level.

The second hypothesis is the existence of non-linearity in the heterogeneity. Specifically, based on the different effect between activity types in the previous section, we speculate that the aggravated sensitivity due to increasing income or pollution will change more slowly, that is to say, because of the existence of inevitable activities or trips, even in the most polluted city the richest people have to maintain a certain percentage of movement, such as work-related activities. To test these hypotheses, we add the squared interactive items of *AvgAQI* and *Income* into the model and present the result in column (4). Obviously, the effect of income is non-linear, i.e., when people become richer their sensitivity to air pollution changes more slowly. However, the role of the squared *AvgAQI* is rejected, indicating that there is no clear non-linearity in the heterogeneity.

Furthermore, we also tested the potential interactive effects of other factors, including urban population size, GDP, holiday, season, temperature, wind, and rain. There is no effect for many of them, as presented in Table 5. Moreover, urban population size generally has no influence when other factors are controlled; for and the interactive term of *GDP* is always significant, however, we believe it reveals the same conclusion as *Income*. The most interesting finding is the role of national *Holiday*, in which urban activities experience an average drop of 6.14% in sensitivity to air pollution and thus causes more exposure risk than on other days. We speculate that the explanation for *Holiday* is the necessity of recreation activities at a medium-long distance.

4.2.2. *Spatial heterogeneity and environmental injustice*

The result above has revealed a complicated environmental injustice situation in China. To provide a clear portrait of that, we

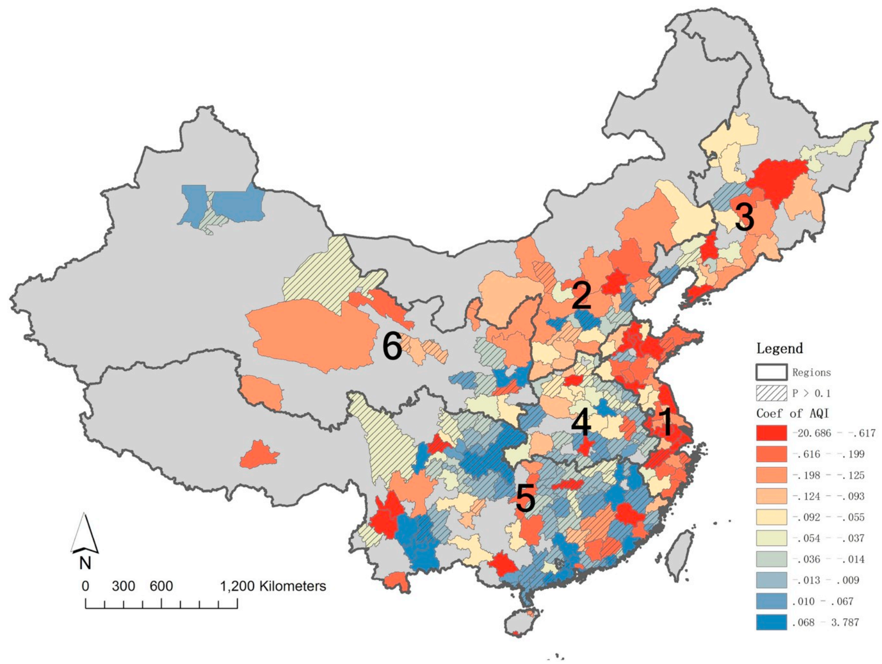

Fig. 4. The coefficients of AQI in each city by varying coefficient model. The cities hatched with diagonal lines indicate non-significant (*P*-value > 0.1) coefficients. The regions are defined by combining the colored patterns and the official division in China.

analyzed the spatial heterogeneity of the effect with Eq. (3) and reported the coefficients of *AQI* in Fig. 4. The map shows clear spatial patterns: (1) the most developed area, including East China (Region 1) and the capital cities of each province, showing the highest sensitivity; (2) North (Region 2), Northeast China (Region 3) and Middle China (Region 4) are next; (3) and the non-capital cities in the broader South (Region 5) and Northwest China (Region 6) have an insignificant correlation or significant but small correlation. Most of the spatial heterogeneity can be explained by *AvgAQI* and *Income*. For instance, the missing adverse impact on urban activity in the third pattern is mainly due to light pollution and underdeveloped economies. Based on the three patterns, we discuss three important environmental injustice issues as follows.

First of all, the spatial patterns explicitly illustrate a new facet of environmental injustice, i.e., the motivation to change the activity pattern in order to protect from air pollution, which has been generally ignored in the literature. When the inequity is measured using the conventional scope – which directly estimates the exposure risk by population, existing studies about China have revealed that developed areas bear a higher environmental burden (He et al., 2017; Ma, 2010). This is in direct contradiction to Western cases (e.g., Bevc et al., 2007) but consistent with our evaluation, for instance, in Table 6 the Proportional Exposure Risk (PER) by population follows the same order as average income. Thus the first three regions are the worst cases and the broader South China is the best one. However, if activity pattern is taken into consideration, the PER by activity shows that citizens in the East Coastal Area may suffer 11% less exposure risk than in North China since they change their activity easily when severe pollution happens. Similarly, in spite of the light pollution, the PER in the Middle and broader South China is underestimated by 3–4% because the people take less action to avoid it. We believe such a new environmental injustice exists not only in developing countries such as China, but also occurs in developed countries. Future studies of certain assessment (e.g., Bäck et al., 2013; Janke, 2014; Mitchell & Dorling, 2003) should carefully incorporate such variance that derives from avoidance behavior.

Moreover, the decisive role of income on the avoidance behavior indicates that the on-going regional development policy in China should be revisited thoroughly to take public health consequences into consideration. Specifically, while considering the effect of air quality alone, such as *AvgAQI*, the situation is partly acceptable because it means that in a more polluted area people will take more actions to avoid exposure risk. However, since *Income* is somehow more effective than *AvgAQI*, as Table 5 shows, current regional development policy becomes a decisive factor. Before 2010, China's economic growth was heavily dependent on facilitating the industrialization of the East Coastal Area, Beijing and its surrounding area, Guangdong province, and the capital cities of the inner provinces. After 2010, first the local governments and then the central government proposed regional balance policies with one focal point of transferring manufacturing from developed cities to other areas, a process known as “industry shift policy” in China. Focusing on service, high-tech, and environmentally-friendly industries, those developed areas benefited from both economic growth and health protection awareness. However, for cities where manufacturing was transferred to, citizens may suffer from both deteriorating air quality and the lack of avoidance behaviors. If this kind of regional balanced-development policy is not combined with public health policy such as spreading the health effects of air pollution and adjusting work schedules in heavy pollution days, then the vision of “economic growth – health problem – protection awareness” should be archived quickly to avoid accumulated health problems. The worst scenario would be that an economic slowdown occurs together with the absence of public health policy and air pollution in the Middle and broader South China increases. Obviously, this problem could be a global lesson for all developing countries with unbalanced regional development.

Finally, there is one more aspect, imperceptible but critical, of environmental injustice in China. That is the general neglect of the detrimental effect of light air pollution. In Fig. 4, we found no significant correlation in many cities as hatched with diagonal lines. Most are located in the Middle, Northwest, or broader South China. Some of them even have a positive coefficient. While the uncommon positive values may be due to a reversed causality that urban activity produces pollution, the general disregard of air pollution could be explained as widespread ignorance of its adverse effects. Although this paper provides no evidence of people's subjective perception about air pollution, we still speculate on a possible linkage between ignorance and China's comparatively low standard/definition of air pollution. For instance, the standard for the World Health Organization's excellent air quality[4] in terms of $PM_{2.5}$ ($\leq 10\ \mu g/m^3$) is defined by the lowest levels at which total, cardiopulmonary and lung cancer mortality have been shown to increase with > 95% confidence in response to long-term exposure. The same definitions in China[5] and the US[6] are $35\ \mu g/m^3$ and $12\ \mu g/m^3$. In Table 6, if we calculate the percentage of days with excellent air quality in the cities of each region based on China's standard, then in Regions 4–6 only half the time qualifies. In contrast, if based on the US standard the appearance of excellent air quality is reduced to nearly 0. We are not saying that the Chinese standard is too low. Instead, we believe it is partly reasonable, as proposed by the WHO document as an "interim target". What we really want to highlight is the necessity and urgency of popularizing the health consequences of air pollution, especially in underdeveloped areas.

5. Conclusion

This paper focuses on a critical problem of contemporary Chinese development: how air pollution affects urban activity. In contrast to the limited literature (Bäck et al., 2013; Graff Zivin & Neidell, 2009; Janke, 2014), we found clear evidence that avoidance behavior exists, and the effect of air pollution varies between pollutants, groups of people, activity types, and air quality alerts. For pollutants, SO_2 has the largest impact on urban activity, followed by $PM_{2.5}$, NO_2, and PM_{10}, while CO and O_3 seem to have little impact. We also revealed more details about the avoidance effect: the effect is at least 4 times smaller among visitors than local residents; the effect on leisure-related activities is about 2–6 times that on work-related activities; and there seems to be a pattern that activities with greater spatio-temporal flexibility can more easily be re-arranged or canceled to reduce exposure risk.

Additionally, we verified several hypotheses about the heterogeneous effect. The result accords well with the circumstantial evidence (Boone et al., 2014; Jerrett et al., 2001; Mitchell & Dorling, 2003; Sun et al., 2017), that increasing *Income* and *AvgAQI* (deteriorative air quality) could lead to higher sensitivity to pollution, while national *Holidays* tend to weaken sensitivity. Thus it reveals the ubiquitous environmental injustice in China between cities. Typically, people who live in more polluted cities, defined as those with 100 unit increments in *AvgAQI*, on average show the same sensitivity as those who live in a less polluted city and earn about 20.3 thousand yuan more in average *Income*. Further tests prove that the interaction effect of *Income* is not linear.

The most important contribution of this paper may be the new insights into environmental injustice based on the empirical evidence. By showing the spatial heterogeneity of the ubiquitous avoidance behavior, we argue that environmental injustice in terms of air pollution, whether in China or in other countries, is not just about the difference in exposure risk measured by pollutant concentration and population distribution, rather it should take urban activity into consideration. At the country scale, conventional estimation (such as He et al., 2017; Ma, 2010) seems to underestimate exposure risk in underdeveloped areas and strongly overestimate in the most developed areas. Moreover, after realizing the crucial role of income in such debate, we argue that the absence of further public health policy on the implementation of a national/regional development policy may lead to new injustice, i.e., huge accumulative health problems, particularly in underdeveloped cities in Middle and broader South China. This problem could be a lesson for all developing countries with unbalanced regional development. Finally, the map also reveals general neglect of the detrimental effect of light air pollution, which we speculate is partly due to China's comparatively low standard of air pollution. The necessity and urgency to popularize the health consequences of air pollution are thereby emphasized.

Finally, we leave the contradictory role of air pollution's impact on urban activity to future discussion. The fundamental starting point of our argument is to take avoidance behavior as a helpful phenomenon to reduce exposure risk when air pollution happens. Obviously, this is true in the short/middle-term view since improving air quality requires significant time and effort. However, from the long-term view, avoidance behavior is never a good thing because it is caused by air pollution. As estimated in this paper, it could be responsible for hundreds of billions of dollars in economic loss. Thus the only and fundamental solution is to eliminate air pollution as much as possible, which of course requires effort and debate far beyond this paper.

[4] World Health Organization, WHO air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide, 2005.

[5] Ministry of Environmental Protection (China), Ambient Air Quality Standards, 2012.

[6] Environmental Protection Agency (US), National Ambient Air Quality Standards, 2012.

Conflict of interest

The authors declare no competing interest.

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