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Does clean air increase the demand for the consumer city? Evidence from Beijing

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Abstract

Cities offer a large menu of possible employment and leisure opportunities. The gains from such consumer city leisure are likely to be lower on more polluted days. We study the association between daily consumption activity and outdoor air pollution in China and find evidence in favor of the hypothesis that clean air and leaving one's home for leisure trips are complements. Given the high levels of air pollution in cities in the developing world, regulation induced improvement in environmental quality is likely to further stimulate demand for the consumer city.

KEYWORDS
consumption, leisure, pollution, restaurant, shopping area

JEL CLASSIFICATION
Q51, Q53, R11, R22

1 | INTRODUCTION

While the average person in China works 64 percent more hours per year than the average person in France, China's urbanites increasingly demand high-quality leisure (Jones & Klenow, 2016). In Beijing, there are dozens of large shopping malls and over 140,000 restaurants. As China's urbanites have more discretionary incomes, they seek out opportunities to visit restaurants to eat and socialize. Such consumer amenities are a major attraction of urban living in China's major cities. In China, 43.1 percent of women work and most urbanites live in small apartments. In a high value of time economy, households engage in less household production and seek leisure activities at shopping malls and restaurants. The ability to socialize is facilitated by more pleasant places for shopping or for dinners. Beijing has excellent public transit within the city such that people can visit a diverse set of alternative locations (Couture, 2016). Access to social media allows people to coordinate with their friends about where they are going to meet. In this sense, Beijing's restaurants and stores represent the coordination mechanisms where social capital is built up (Glaeser & Gottlieb, 2006; Glaeser, Laibson, & Sacerdote, 2002).

The consumer city literature has mainly focused on the retail, culture, and leisure opportunities available across cities in the United States (Couture, 2016; Couture & Handbury, 2017; Glaeser, Kolko, & Saiz, 2001; Handbury & Weinstein, 2014). Studies examine how population density (Schiff, 2014), transportation accessibility (Schuetz, 2015; Zheng, Xu, Zhang, & Wang, 2016), segregation and crime (Davis, Dingel, Monras, & Morales, 2017), and weather and climate (Agarwal, Jensen, & Monte, 2017; Chan & Wichman, 2018) influence the consumption of non-tradable goods and services in cities. A key driver of consumption amenities in cities is the ability to live in close proximity with people with similar tastes. Waldfogel (2008) argues that in the presence of fixed costs of selling a given non-tradeable variety of a product, a firm will enter a market and offer the variety only if there is sufficient local demand to drive down average fixed costs. In his model, such consumption choices are independent decisions. In the case of China, socializing through joint leisure trips is a major part of daily life. Groups of friends gain from going out together, which creates opportunities for retailers and restaurants to cater to such individuals.

Many of China's cities are extremely polluted (Kahn & Zheng, 2016). Such pollution may inhibit leisure activity as people engage in averting behavior. Recent studies have documented that people are more likely to stay inside if they are aware of the high extent of outdoor pollution (Graff-Zivin & Neidell, 2009; Neidell, 2009). He, Luo, and Zhang (2017) find that air pollution has negative impacts on both daily movie audiences and revenue in Chinese cities.

In this paper, we test whether the demand for the urban consumer city will increase when air pollution is lower. When Chinese urbanites remain at home on polluted days, this self-protection lowers their exposure to pollution but at the same time lowers the urbanites' consumer surplus from living in a vibrant city. Restaurants and retailers lose profits on those days when households stay home. This "pollution tax" lowers the expected revenue for restaurants.

To study the leisure complementarity between clean air and urban consumption, we use two big-data sets focused on daily activities within Beijing China. The first is online review data from *Dianping.com* (China's version of *Yelp.com*) and the second is the mobile positioning data from the *Tencent* Company. We estimate negative binomial models to study how leisure trips are affected by daily outdoor air pollution. We also introduce a regression discontinuity design (RDD) to test how government announcements of high-pollution days affect people's demand for restaurants.

We find that air pollution reduces residents' visits to the restaurant (proxied by review counts) and shopping area although the average effect is not large. Our nonlinear regression results show that restaurant and shopping area visits will decline by roughly 1.6 and 2.8 percent respectively, if $PM_{2.5}$ concentration level rises from the 25th percentile to 75th percentile (40 $\mu g/m^3$ to 120 $\mu g/m^3$; 25 $\mu g/m^3$ to 94 $\mu g/m^3$ for these two samples). We find that the negative effects are larger on hotter days. On hot days (the temperature exceeds its 80th percentile), the decline magnitudes of the restaurant and shopping area visits become 4–5 times larger for the same marginal increase in $PM_{2.5}$ concentration. On the basis of our RDD estimates, we find that restaurant visits drop by roughly 4 percent at the "dirty day" cutoff (air quality is "heavily polluted" or "severely polluted"), which is mostly attributed to consumers' averting behavior as they anticipate thanks to a government announcement that a high pollution day will occur soon. They respond by altering their plans. We also observe a large "rebound effect" such that, after several polluted days during which consumer leisure demand is suppressed, dining-out and shopping activities experience a boost on the first subsequent "blue sky day" (air quality is "good" or "excellent"). This intertemporal substitution highlights how Beijing residents adapt to the environmental conditions they face. Since we know the online ratings of the restaurants, we are able to classify them by quality and we find that higher-quality restaurants experience a larger drop in demand on more polluted days than lower-quality restaurants.

Our finding that there is a complementarity between clean air and private sector investment and enjoyment of the Beijing consumer city has implications for the benefits from regulation that mitigates pollution externalities. In cities around the United States, such as Boston and Cleveland, improvements in nightlife and dining options have emerged in downtown areas that have experienced sharp improvements in environmental quality. For example, in downtown Cleveland, there has been a growth in excellent restaurants adjacent to Cleveland's pretty Cuyahoga River (that caught on fire in 1969 because of its high level of water pollution).

Environmental economics research measuring the gains from pollution regulation typically focuses on the health gains (Chay & Greenstone, 2003) or the reductions in private self-protection, such as medical expenditures (Deschênes, Greenstone, & Shapiro, 2017). Our research highlights that there are consumer surplus gains from the enhanced consumer city because of pollution reductions. A micro-founded model of the marginal utility from leisure trips that includes an interaction term such that the marginal utility from restaurants is lower on more polluted days yields behavioral predictions that match our empirical findings.

1.1 | The Beijing air pollution challenge

In Figures 1 to 3, we report the $PM_{2.5}$ data in Beijing released by the Chinese Ministry of Environmental Protection (MEP). Figure 1 highlights that while air quality has been improving in Beijing, the $PM_{2.5}$ concentration level in recent years has been roughly four to five times higher than that in New York City and Los Angeles in the United States.

Figure 2 displays the distribution of Beijing's $PM_{2.5}$ concentration in each quarter of our study periods (the restaurant analysis is on the basis of the data from January 2013 to December 2014; the shopping area analysis is on the basis of the data from December 2015 to April 2017). The city suffers from higher levels of pollution in winter and spring because central heating is provided by coal-fired power plants and a weather inversion occurs which traps air pollution. Figure 3 shows the significant spatial variation of $PM_{2.5}$ concentration across districts of Beijing. The $PM_{2.5}$ concentration is higher in the western and southern districts.

The pollution that Beijing's residents are exposed to is the overall result of motorization, winter heating, and industrial activities in surrounding areas (Ebenstein, Fan, Greenstone, He, & Zhou, 2017; Zheng & Kahn, 2017). The sharp growth in motorization using high sulfur gasoline and the use of diesel trucks have all contributed to elevated urban air pollution levels (Ebenstein et al., 2015; Fang, Chan, & Yao, 2009).

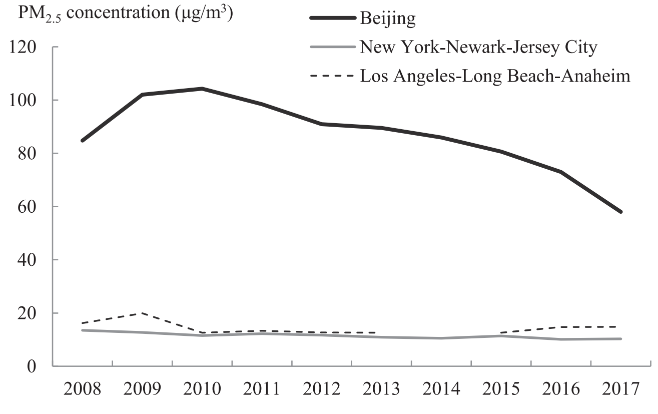

FIGURE 1 Yearly mean $PM_{2.5}$ concentration levels in Beijing, New York, and Los Angeles, Note: The original data of Beijing's $PM_{2.5}$ concentration is daily readings, from Chinese Ministry of Environmental Protection (2013–2017) and the United States Embassy (2008–2012). We calculate the yearly average values of these daily readings. The yearly mean $PM_{2.5}$ concentrations of New York and Los Angeles are from the Environmental Protection Agency in the United States

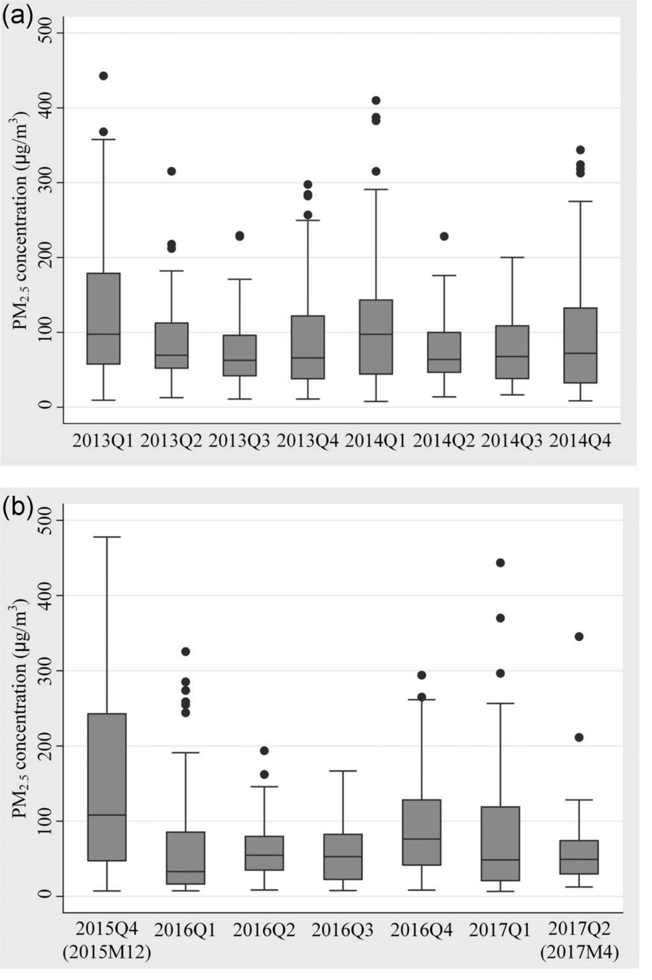

FIGURE 2 Beijing's $PM_{2.5}$ concentration of each year-and-quarter, (a) Restaurant Study period from the first quarter of 2013 to the fourth quarter of 2014), (b) shopping area study period from the fourth quarter of 2015 to the second quarter of 2017

The epidemiology literature has established that air pollution exposure has a direct effect on raising mortality and morbidity risk as it increases the incidence of lung cancer, cardio-respiratory diseases, and lowers infant birth weight (Almond, Chen, Greenstone, & Li, 2009; Currie & Neidell, 2005; He, Fan, & Zhou, 2016; Pope et al., 2011). Recent research has documented that air pollution exposure also reduces workers' productivity (Chang, Graff Zivin, Gross, & Neidell, 2016; Chang, Graff Zivin, Gross, & Neidell, 2019; Graff Zivin & Neidell, 2012; Neidell, 2017; Wu & Reimer, 2016), lowers people's cognitive competence and students' test performance (Currie, Zivin, Mullins, & Neidell, 2014; Zhang, Chen, & Zhang, 2018), as well as affects the real-time well-being and the long-run human capital acquisition (Bharadwaj, Gibson, Zivin, & Neilson, 2017; Zheng, Wang, Sun, Zhang, & Kahn, 2019).

1.2 | Urban trip demand and local air pollution

Self-protection strategies, such as wearing masks, using air purifiers and staying inside, can lower people's exposure to pollution (Sun, Kahn, & Zheng, 2017; Zhang & Mu, 2018; Zhang, Sun, Liu, & Zheng, 2016), whereas it also lowers their consumer surplus as they lose access to their city's diverse set of shopping and socializing opportunities.

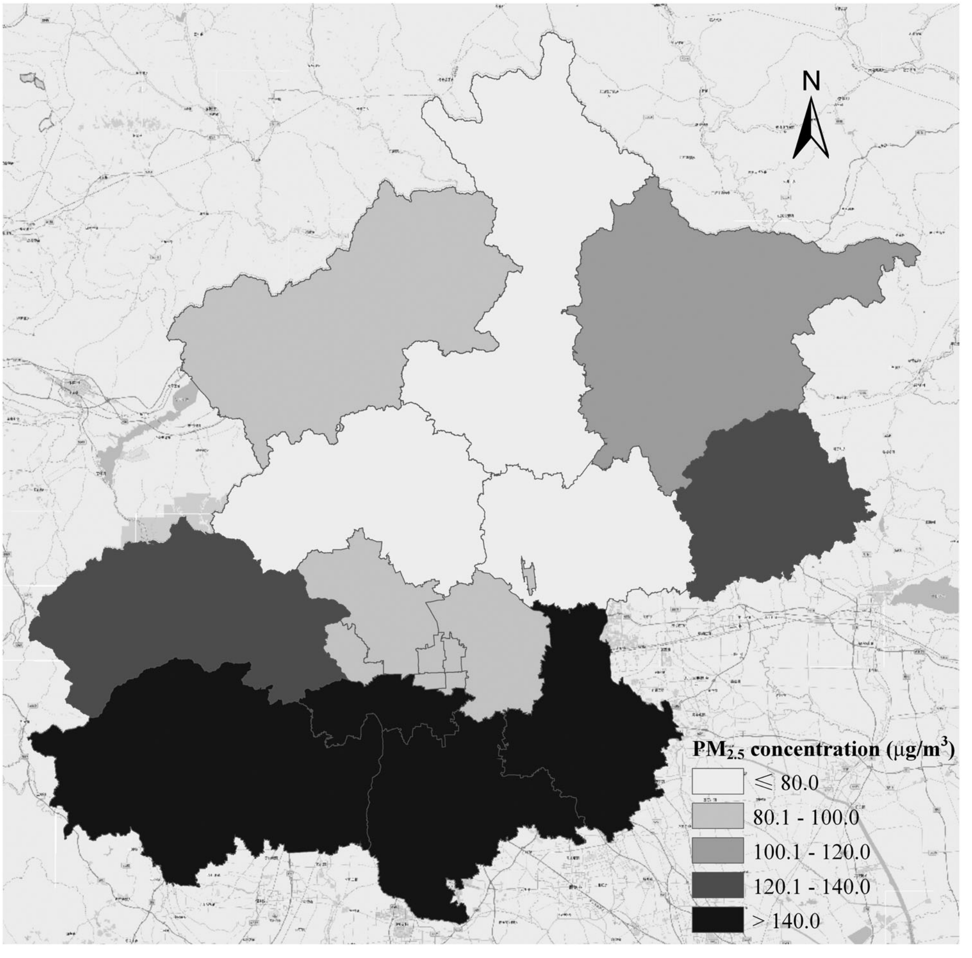

FIGURE 3 Beijing's $PM_{2.5}$ concentration distribution by district (from January 2013 to April 2017)

To motivate our empirical work, we introduce a simple demand framework to highlight the linkages of interest. We assume that each person has the same utility function and takes the local ambient pollution level as exogenously given. A person gains utility from consuming food, being exposed to clean air, consuming other goods besides food, and spending time with her friend network (see Equation (1)). The utility that the network brings is an increasing function of how many friends are joining her in social activity. We assume that one's friends are less likely to go outside on a polluted day. Therefore, in Equation (2), g is a decreasing function of pollution. Substituting Equation (2) into the utility function and taking a derivative with respect to outdoor pollution yields Equation (3). We assume that food consumption and clean air are complements and socializing with friends and clean air are also complements.

$$U = U(Network, Food, Pollution, C); \tag{1}$$

$$Network = g(Pollution); \tag{2}$$

Therefore,

$$\frac{dU}{dPollution} = \frac{\partial U}{\partial Pollution} + \frac{\partial U}{\partial Network} \times \frac{\partial Network}{\partial Pollution}. \tag{3}$$

Equation (3) highlights that pollution has two effects on a person's well being. First, there is a direct negative effect of pollution on utility. The second term in Equation (3) captures the chain effect that outdoor pollution leads people to stay at home and hunker down, which reduces the possibilities of jointly enjoying the consumer city with one's friends. Therefore, the urban consumption activity may experience a decline on polluted days. We recognize that a counter-veiling point is that restaurants together with roads to those restaurants may be less congested on polluted days, and this reduction in congestion might make such locations more attractive to visit on polluted days. This is ultimately an empirical issue.

2 | EMPIRICAL FRAMEWORK AND DATA

2.1 | Dining-out and shopping data

Over the past 10 years, Beijing residents' consumption opportunities have dramatically improved as people have increased access to shopping malls and a greater variety of restaurants. People have responded by altering their leisure activities and social networking activities.

We test how the daily outdoor leisure activity in Beijing is associated with pollution and climate conditions. We use two data sets to respectively describe Beijing residents' dining-out and shopping activities. The first data set comes from the largest restaurant platform *Dianping.com* in China. The platform, established in 2003, provides several services that create a type of "consumer guide" similar to Yelp in the United States. The information of each restaurant we obtain includes its detailed attributes, users' check-ins, and their reviews and ratings from 2004 to the present. By the second quarter of 2016, *Dianping* had more than 250 million active users, around 8 million restaurants, and 125 million reviews on those restaurants.

Because we cannot access the customer visit count to each restaurant by date, we instead rely on a count measure of how many customers publish their reviews on the *Dianping* website during or after their dinners. We observe the date for which the review is posted. Our review data includes 4,803 restaurants and 1.89 million customer reviews in Beijing.[1] We compile each restaurant's daily amount of reviews from January 2013 to December 2014 for our individual-level analysis. Below, we use several of the attributes of a restaurant in our analysis.

The *Dianping* data set provides a rich set of attributes of restaurants, such as type (fast food or not), cuisine, and quality (ratings), so that we are able to look into the heterogeneous effects of pollution on a dining-out activity for various population groups who have different preferences for restaurants.

We recognize that by using the count of reviews as a proxy for the count of restaurant visits, we implicitly assume that the probability of writing a review is not a function of the outdoor pollution level. If customers are less likely to write reviews on polluted days although some of them still dine out in restaurants, the negative impact of pollution on restaurant visits will be overestimated, and vice versa. Customers may also not write reviews on the same day they eat in the restaurant. We address this concern by averaging the current day and the next day's review counts and use the average value as another proxy for current day's visits. The results are robust to this measure.

The second data set is a large-scale mobile phone positioning data set. This data set comes from the *Tencent* Company, which is one of China's largest online social platform providers. It is also the leading e-pay service developer, world-class mobile game operator, and a well-known digital map and navigation developer. With this market niche, *Tencent* tracks the real-time location information through its various Internet services for each of more than 800 million active users. We access the daily count of people in four representative shopping areas during the time period from December 2015 to April 2017 (national holidays are not included in this data

[1]To avoid the bias caused by the restaurants with very few reviews, the restaurants with less than 100 online reviews in the period are excluded from our sample.

sample).[2] This positioning data set is used to supplement the analysis of the impact of air pollution on leisure behavior.[3]

2.2 | Air quality data

The daily air pollution data is obtained from MEP. MEP reports each monitoring station's hourly concentration of various air pollutants. Because the spatial variation in $PM_{2.5}$ across districts is significant (see Figure 3), we calculate the daily mean value of $PM_{2.5}$ concentration in each district of Beijing for the period from January 2013 to April 2017,[4] and then merge it with the restaurants/shopping area in the corresponding district. The high-frequency temporal changes in $PM_{2.5}$, together with the cross-district spatial variation, help to identify $PM_{2.5}$'s negative effects on dining-out and shopping activities.

The MEP has created a discrete set of codes for classifying days according to whether a given day is highly polluted or not. According to China's new Ambient Air Quality Standards (GB3095-2012) released by the MEP, there are six pollution levels: Excellent, good, lightly polluted, moderately polluted, heavily polluted, and severely polluted. In our study period, the MEP and local environmental protection bureaus released the daily pollution level to the public on the same day. They group days with "excellent" and "good" air quality together and call them "blue sky days" ($PM_{2.5}$ concentration $<75\,\mu g/m^3$), and we also group days with "heavily polluted" and "severely polluted" air quality together and call them "dirty days" ($PM_{2.5}$ concentration $>150\,\mu g/m^3$). As the quality of China's official air pollution data has been questioned (Ghanem & Zhang, 2014), we also collect the additional $PM_{2.5}$ data from the United States Embassy in Beijing, and use it for a robustness check.[5]

2.3 | Weather data

We collect Beijing's historical weather data from the National Oceanic and Atmospheric Administration (NOAA), which provides information from global weather stations included in the National Climatic Data Center (NCDC) of NOAA.

2.4 | The empirical framework

We estimate Equation (4) using a negative binomial model to test how the count of the leisure activity varies as a function of outdoor air pollution and climate conditions,[6]

$$NUM_{idt} = \alpha_0 + \alpha_1 \ln(PM_{dt}) + \alpha_2 \ln(PM_{dt}) \times TEMP_t + \boldsymbol{\alpha_3 W_t} + \boldsymbol{\alpha_4 X_{idt}} + \eta_t + \lambda_{id} + \varepsilon_{idt}. \quad (4)$$

[2]In this paper, the shopping area refers to a large shopping mall with its surrounding area. Shopping area A is located near Beijing's city center (about 14,000 m^2), shopping area B is located in the sub-center (about 19,000 m^2), shopping area C is located near the transport hub (about 22,000 m^2), and shopping area D is located near some international communities (about 68,000 m^2).

[3]Unfortunately, the resolution of that *Tencent* mobile phone positioning data is not high enough to identify an individual restaurant's spatial boundary and thus is unable to yield the count measure of visits to an individual restaurant. We conduct various robustness checks and also compare the magnitudes of the effects with those on the basis of the shopping area regressions.

[4]As most shopping and dining-out activities occur in daytime or early evening, $PM_{2.5}$ concentration readings during late night time (6:00 p.m. on the day to 4:00 a.m. of the next day) are excluded when calculating the daily mean value.

[5]The recent MEP official $PM_{2.5}$ data and the US embassy $PM_{2.5}$ data provide consistent readings. The correlation coefficient between these two $PM_{2.5}$ data is about 0.98.

[6]As there is a lot of zero values for individual restaurant visits, we use a zero-inflated negative binomial model in the baseline estimates, and later use a standard negative binomial model to check the robustness of the results in the Appendix.

where the subscript i indicates the restaurant/shopping area, d is district, and t is the date. The dependent variable NUM_{idt} measures the total review count for restaurant i in district d on day t when we use the *Dianping* data, whereas it measures the total count of the activity in shopping area i in district d on day t when we use the *Tencent* data. PM_{dt} is the mean $PM_{2.5}$ concentration of district d on day t, and we use its log form in our model.[7] We expect the coefficient α_1 to be negative – if the air quality becomes worse ($PM_{2.5}$ level becomes higher), people will be more likely to take fewer leisure trips to restaurants and shopping areas. In some regressions we report below, instead of using the continuous measure of $PM_{2.5}$ concentration, we use dummy variables that indicate whether a day is a "dirty day" or a "blue sky day". We test whether these pollution effects vary as a function of outdoor temperature and vary by types of restaurants. In an additional specification, we include the level and quadratic terms of PM_{dt} to test for the nonlinear relationship.

$\mathbf{W_t}$ is a vector of typical weather condition controls including daily mean temperature, wind speed, and precipitation. $\mathbf{X_{idt}}$ is a vector of other control variables. Year-and-quarter fixed effects and day-of-week dummies η_t are included to control for the seasonality effect and the difference of leisure activities among quarters and weekdays.[8] We use fixed effects λ_{id} to control for time-invariant unobservables that vary across restaurant/shopping area (i) as well as district (d).[9] ε_{idt} is a disturbance term. The standard errors are clustered by the restaurant/shopping area.

After presenting our baseline results, we estimate additional models to explore the possible mechanisms. First, we employ an instrumental variable (IV) approach and RDD to infer the causal impacts. Unobserved variables may raise endogeneity issues. For instance, booming production activities in the city may lead to both higher air pollution and higher income (or more leisure activities) for workers. In our IV approach, we follow Zheng, Cao, Kahn, and Sun (2014) and Zheng et al. (2019) and use the particulate matters in nearby cities to construct a "cross-boundary spillovers" IV for Beijing's local $PM_{2.5}$ concentration level, as a large portion of the particulate matters in Beijing's air is blown by the wind from nearby industrial cities in Hebei Province and other provinces. In our RDD approach, we investigate whether there is a sharp drop in leisure activities at the "dirty day" cutoff (150 μg/m^3), see Equation (5). We augment our baseline model by including a dummy of "dirty day" (D) and quadratic/cubic polynomials for forcing variable ($M = PM2.5 – 150$ μg/m^3) and set different bandwidths (h) around the "dirty day" threshold (150 μg/m^3).[10] We expect that the coefficient of D is negative, which indicates the causal impact at the point of the discontinuity. Other covariates, such as weather conditions, time fixed effects, and area fixed effects are also included in the IV and RDD estimates.

$$\begin{aligned} &NUM_{idt} = \beta_0 + \beta_1 D + \beta_2 f\,(M_{dt}) + \beta_3 D \times f\,(M_{dt}) + \boldsymbol{\beta_3 W_t} + \boldsymbol{\beta_4 X_{idt}} + \eta_t + \lambda_{id} + \varepsilon_{idt} \\ &\text{where } M_{dt} = PM_{dt} - 150\mu g/m^3, \quad M_{dt} \in [-h, +h]. \end{aligned} \tag{5}$$

Second, we examine if a "rebound effect" exists – after multiple polluted days, whether consumers make up for their lost leisure time by going out more on a subsequent blue-sky day? The rebound effect is expected to be larger after more consecutive polluted days. Third, we use the interaction terms of $PM_{2.5}$ and restaurant attributes (rating, cuisine, and type) to test for the heterogeneous effects of air pollution by examining whether high-quality

[7]There are 18 districts in Beijing, and Beijing Environmental Protection Bureau reports daily $PM_{2.5}$ concentration for each district and also for the whole city. This spatial variation in air pollution gives us some more degree of freedom to identify its negative impact on restaurant visits. For shopping area regressions, since we only have four shopping areas, we are unable to include district fixed effects. We still have shopping area fixed effects (three dummies), and assign the district-specific $PM_{2.5}$ readings to the shopping area in that district.

[8]We choose to include the year-and-quarter fixed effects (instead of monthly fixed effects) because of two reasons: First, the $PM_{2.5}$ concentration variation is significantly smaller within a quarter than within a year. We use the year-and-quarter fixed effects to control such seasonality. Second, monthly fixed effects will absorb too much of the temporal variation. Because the spatial variation is relatively low (only 18 districts for restaurants and four places for shopping areas), we still need to rely on this temporal variation to identify $PM_{2.5}$'s effect.

[9]In the restaurant negative binomial regression, for the sake of computational efficiency, we include 18 district fixed effects (instead of 4,803 restaurant fixed effects). As $PM_{2.5}$ does not vary across locations within a district, the estimated coefficients are not sensitive to the choice of fixed effects.

[10]Gelman and Imbens (2018) recommend the use of low-order polynomials in the RDD.

restaurants and dine-in restaurants (supposed to have more intense social interactions) suffer a greater loss in business on polluted days.[11]

The variable definitions and summary statistics are presented in Table 1.

3 | EMPIRICAL RESULTS

3.1 | Baseline results on restaurant visit count

Table 2 reports our baseline estimates of Equation (4) using the restaurant data set. Since the dependent variable (daily visits to a restaurant) is a count variable and it is zero or a small value for most of the restaurants, we estimate a zero-inflated negative binomial model (standard negative binomial estimates are in the Appendix). In the first column, the coefficient of *PM2.5* is negative and statistically significant. An incidence-rate ratio calculation shows a small negative elasticity of $PM_{2.5}$. A 10 percent increase in the $PM_{2.5}$ concentration is associated with a 0.15 percent decrease in restaurant visits (proxied by the number of reviews on *Dianping.com*). Another way to interpret this magnitude is, restaurant visits decline by roughly 1.0 percent if the $PM_{2.5}$ concentration level rises from its 25th percentile (40 $\mu g/m^3$) to 75th percentile (120 $\mu g/m^3$). Restaurant visits drop on both hot and windy days, whereas the rain effect is not statistically significant. Restaurants are much busier on weekends.

In the next two columns, we examine the interaction effect of air pollution and temperature or hot weather. In column (2) we add the interaction term of $PM_{2.5}$ with temperature, and the coefficient is significant and negative. It means that the $PM_{2.5}$ can have a larger negative impact on restaurant visits can be larger when the temperature is higher. We then replace this continuous temperature variable with two heat dummies in column (3) – "*Heat_level1*" dummy indicates the temperature falling between the 60th quantile and the 80th quantile of temperature distribution in our sample, and "*Heat_level2*" dummy indicates the temperature exceeding the 80th quantile. The coefficients on both of the interaction terms are negative and statistically significant. This indicates that air pollution's negative impact is exacerbated on hot days – the magnitude is about 3–4 times larger for the same amount of the $PM_{2.5}$ concentration level increase.

To explore the nonlinearity of the relationship between $PM_{2.5}$ concentration and restaurant visits, we include the level and squared terms of *PM2.5* in the last column. It shows a monotonic negative relationship between $PM_{2.5}$ concentration and restaurant visit count. An intuitive way to interpret this magnitude is, restaurant visits decline by roughly 1.6 percent if the $PM_{2.5}$ concentration level rises from its 25th percentile (40 $\mu g/m^3$) to 75th percentile (120 $\mu g/m^3$). We further estimate the Kernel-based semiparametric model to investigate the nonlinear relationship between daily visit for each restaurant and $PM_{2.5}$ concentration (Figure 4). *PM2.5* is estimated as a non-parametric component and other variables as parametric components. We observe a negative relationship again in this Kernel-based $PM_{2.5}$–visits curve. There are very few observations on heavily polluted days at the far-right end, so the confidence interval becomes much larger there.

We conduct two robustness checks in the Appendix (Table A2). The first one tests for the reliability of the official $PM_{2.5}$ data. We replace the MEP $PM_{2.5}$ data with the U.S. Embassy $PM_{2.5}$ data (from a single monitor on the Embassy's roof, near CBD) in the baseline regression. The coefficient of ln(*PM2.5_US Embassy*) is still negative and statistically significant. Second, we drop the observations during the APEC China 2014 when some temporary command-and-control harsh regulations on firms and traffic were imposed. The magnitude and significance of the coefficient of ln(*PM2.5*) are consistent with our baseline results.

[11]Some restaurants have missing attributes. In this case, we categorize them as other cuisine or type.

TABLE 1 Variables and summary statistics

Panel A: Restaurant (January 2013 to December 2014)					
Variable	**Obs.**	**Mean**	**Std.**	**Min**	**Max**
Daily count	3,143,813	0.413	1.126	0	90
PM2.5 (100 μg/m^3)	3,143,813	0.916	0.726	0.030	5.000
PM2.5_US Embassy (100 μg/m^3)	3,070,244	0.987	0.809	0.065	5.686
Temperature, °C	3,143,813	13.796	10.810	−9.2	31.9
Extreme heat (1 = *Temperature* ∈ (80%,100%])	3,143,813	0.201	0.400	0	1
Wind speed, m/s	3,143,813	7.753	2.911	2	25
Precipitation, mm	3,143,813	1.464	6.028	0	85.09
Dirty day (1 = Heavily or severely polluted)	3,143,813	0.155	0.362	0	1
Blue sky (1 = Air quality is excellent or good)	3,143,813	0.519	0.500	0	1
NEIGHBOR	3,040,472	0.608	0.575	0.078	5.863
TCI	3,119,348	0.550	0.195	0.11	0.91
Heating	3,143,813	0.331	0.470	0	1
Score_overall (0–100)	3,143,813	72.558	8.185	27.058	96.344
Score_taste (0–100)	3,143,813	74.361	7.410	34.833	95.637
Score_environment (0–100)	3,143,813	71.902	9.618	30.128	96.108
Score_service (0–100)	3,143,813	70.551	9.170	28.642	97.877
Cuisine_Chinese (1 = cuisine is Chinese)	3,143,813	0.431	0.495	0	1
Cuisine_Foreign (1 = cuisine is Foreign)	3,143,813	0.216	0.411	0	1
Cuisine_Missing (1 = cuisine is missing)	3,143,813	0.353	0.478	0	1
Type_Fast (1 = type is Fast food)	3,143,813	0.206	0.404	0	1
Type_Nonfast (1 = type is Non-fast food)	3,143,813	0.723	0.448	0	1
Type_Missing (1 = type is missing)	3,143,813	0.071	0.258	0	1
Panel B: Shopping area (December 2015 to April 2017)					
Variable	**Obs.**	**Mean**	**Std.**	**Min**	**Max**
Daily visits (overall shopping areas)	1,868	35884.5	15375.0	10491	102708
PM2.5 (100 μg/m^3)	1,868	0.726	0.682	0.066	4.778
PM2.5_US Embassy (100 μg/m^3)	1,744	0.741	0.716	0.055	5.373
Temperature, °C	1,868	11.838	10.857	−14.1	31.2
Extreme heat (1 = *Temperature* ∈ (80%, 100%])	1,868	0.201	0.401	0	1
Wind speed, m/s	1,868	11.136	5.666	3.9	39.6
Precipitation, mm	1,868	1.442	12.690	0	262.64
Dirty day (1 = Heavily or severely polluted)	1,868	0.109	0.312	0	1
NEIGHBOR	1,864	0.344	0.260	0.076	2.700

3.2 | Baseline results on shopping area visits

We examine the impact of air quality on shopping area visits. Table 3 reports our baseline estimate results. The dependent variable is the count of daily visits to a shopping area. Those shopping areas are relatively big so the dependent variable value is non-zero. Therefore, we employ the standard negative binomial estimator. Each column in Table 3 reports a separate regression with shopping area fixed effects.

TABLE 2 Effect of air pollution on the restaurant visit count

Dependent variable: *Daily count*	(1)	(2)	(3)	(4)
ln(*PM2.5*)	−0.0152***	0.00668***	0.00129	
	(0.00183)	(0.00251)	(0.00199)	
ln(*PM2.5*)**Temperature*		−0.00203***		
		(0.000177)		
ln(*PM2.5*)**Heat_level1*			−0.0788***	
			(0.00646)	
ln(*PM2.5*)**Heat_level2*			−0.0600***	
			(0.00494)	
PM2.5				−0.00951*
				(0.00566)
$(PM2.5)^2$				−0.00701***
				(0.00170)
Temperature	−0.0165***	−0.0173***	−0.0170***	−0.0164***
	(0.000658)	(0.000669)	(0.000658)	(0.000652)
Wind speed	−0.00517***	−0.00375***	−0.00358***	−0.00569***
	(0.000512)	(0.000527)	(0.000510)	(0.000500)
Precipitation	−0.000103	0.000217	0.000301	−0.000108
	(0.000186)	(0.000188)	(0.000193)	(0.000186)
Day-of-week dummies:				
Default: *Wednesday* (1 = Wednesday)				
Monday (1 = Monday)	0.0924***	0.0900***	0.0909***	0.0911***
	(0.00459)	(0.00459)	(0.00460)	(0.00461)
Tuesday (1 = Tuesday)	0.0303***	0.0301***	0.0327***	0.0292***
	(0.00312)	(0.00311)	(0.00318)	(0.00315)
Thursday (1 = Thursday)	0.0408***	0.0457***	0.0510***	0.0435***
	(0.00310)	(0.00314)	(0.00327)	(0.00315)
Friday (1 = Friday)	0.107***	0.111***	0.114***	0.107***
	(0.00592)	(0.00602)	(0.00609)	(0.00598)
Saturday (1 = Saturday)	0.212***	0.215***	0.218***	0.215***
	(0.00880)	(0.00889)	(0.00901)	(0.00891)
Sunday (1 = Sunday)	0.201***	0.200***	0.206***	0.200***
	(0.00755)	(0.00754)	(0.00769)	(0.00759)
Constant	−1.201***	−1.211***	−1.215***	−1.162***
	(0.123)	(0.123)	(0.123)	(0.122)
District fixed effects	Yes	Yes	Yes	Yes
Year-and-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	3,143,813	3,143,813	3,143,813	3,143,813
Restaurant number	4,803	4,803	4,803	4,803

In column (3), we include "*Heat_level1*" dummy indicating whether the temperature is between the 60th quantile and the 80th quantile or not, and "*Heat_level2*" dummy indicating whether the temperature exceeds the 80th quantile or not; Standard errors in parentheses are clustered by the restaurant; **$p < 0.05$

*$p < 0.1$.

***$p < 0.01$.

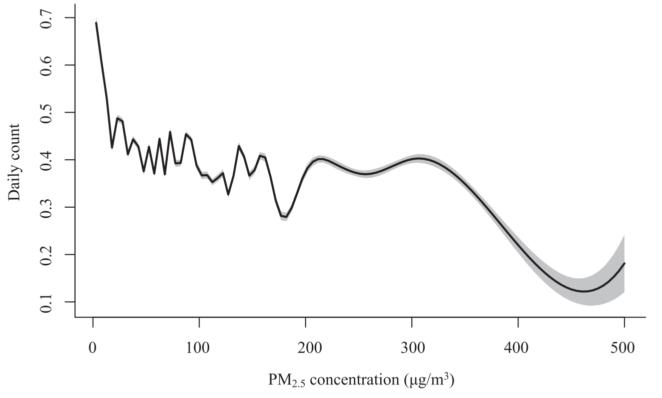

FIGURE 4 Kernel-based estimation of the semiparametric restaurant regression, *Note:* The specification of this semiparametric regression is similar to the results reported in Table 2's column (1), in which ln(*PM2.5*) is replaced with a non-parametric component in this semiparametric model. The unit of analysis is a restaurant-day. The black curve is the nonparametric fit curve showing the nonlinear relationship, and the gray area shows the confidence interval around the nonparametric fit

As shown in column (a), an incidence-rate ratio calculation shows that shopping area visits will decrease by 0.09 percent if $PM_{2.5}$ concentration increases by 10 percent. This magnitude is slightly smaller than that in our baseline restaurant visits regression (which is 0.15). Another interpretation is, all else equal, the shopping area visits will decline by roughly 1.2 percent if the $PM_{2.5}$ concentration rises from its 25th percentile value (25 $\mu g/m^3$) to the 75th percentile value (94 $\mu g/m^3$). In columns (b) and (c), similar to our restaurant results, the negative impact of $PM_{2.5}$ on shopping area visits is exacerbated on hot days. On very hot days when the temperature exceeds the 80th percentile of temperature distribution, the size of this negative impact becomes 4.7 times larger. In column (d), we include *PM2.5* and its quadratic term to detect the nonlinear relationship between $PM_{2.5}$ concentration and shopping area visits. We observe a U-shape but roughly 90 percent of the observations are on the left-hand side. One possible explanation for the small upswing after this turning point is that when it is very polluted outdoors, some large and high-end shopping malls will turn on their air purification systems to attract customers.[12] According to this nonlinear estimate, the shopping area visits will decline by roughly 2.8 percent if the $PM_{2.5}$ concentration rises from its 25th percentile value (25 $\mu g/m^3$) to the 75th percentile value (94 $\mu g/m^3$). Similarly, on very hot days those shopping malls will also turn on their air conditioning. This may explain why the temperature variable itself is statistically insignificant. Shopping areas lose customers on rainy and windy days. These findings are robust even if we switch and use the U.S. Embassy $PM_{2.5}$ data (Table A2).

3.3 | RDD and IV estimates

Some potentially omitted variables, such as local economic activities, may affect the local air quality and residents' leisure activity simultaneously. We include a rich set of fixed effects (restaurant/shopping area, district, year-and-quarter FEs) to control for such unobservables. In addition, we employ two approaches – a RDD and an IV strategy – to address this endogeneity issue and to attempt to infer the causal impact of $PM_{2.5}$ pollution on a leisure activity.

In the RDD approach, the cutoff value is set at the "dirty day" threshold (150 $\mu g/m^3$). We estimate Equation (5) to detect if there is a discontinuity in leisure activities at this cutoff. Panel A of Table 4 reports the RDD estimates. For restaurant visits, we choose two bandwidths (h = 30 $\mu g/m^3$and 50 $\mu g/m^3$), and include separate polynomials for values of $PM_{2.5}$ concentration above and below the dirty day threshold (quadratic for the narrower bandwidth and

[12]See some evidence from this news piece on Financial Times: https://www.ft.com/content/e25219d8-d3a9–11e6–9341-7393bb2e1b51

TABLE 3 Effect of air pollution on the shopping area visits

Dependent variable: *Daily visits*	(1)	(2)	(3)	(4)
ln(*PM2.5*)	−0.00904**	0.00794**	−0.00243	
	(0.00352)	(0.00387)	(0.00538)	
ln(*PM2.5*)**Temperature*		−0.00166***		
		(0.000336)		
ln(*PM2.5*)**Heat_level1*			−0.00320	
			(0.00447)	
ln(*PM2.5*)**Heat_level2*			−0.0437***	
			(0.0140)	
PM2.5				−0.0685***
				(0.00720)
$(PM2.5)^2$				0.0229***
				(0.00164)
Temperature	0.00189	0.000888	0.00135	0.00206
	(0.00140)	(0.00132)	(0.00155)	(0.00141)
Wind speed	−0.00317***	−0.00223***	−0.00280***	−0.00338***
	(0.000724)	(0.000639)	(0.000811)	(0.000679)
Precipitation	−0.000596***	−0.000603***	−0.000501***	−0.000597***
	(0.000115)	(0.000114)	(0.0000858)	(0.000111)
Day-of-week dummies:				
Default: *Wednesday* (1 = Wednesday)				
Monday (1 = Monday)	−0.0239***	−0.0213***	−0.0234***	−0.0236***
	(0.00380)	(0.00350)	(0.00408)	(0.00398)
Tuesday (1 = Tuesday)	−0.000905	−0.00121	−0.00139	−0.00633
	(0.00533)	(0.00538)	(0.00540)	(0.00512)
Thursday (1 = Thursday)	0.0145***	0.0148***	0.0131***	0.0143***
	(0.00305)	(0.00311)	(0.00288)	(0.00311)
Friday (1 = Friday)	0.0938***	0.0933***	0.0921***	0.0888***
	(0.00886)	(0.00884)	(0.00832)	(0.00853)
Saturday (1 = Saturday)	0.171	0.170	0.169	0.171
	(0.117)	(0.117)	(0.116)	(0.117)
Sunday (1 = Sunday)	0.109	0.109	0.108	0.108
	(0.117)	(0.117)	(0.117)	(0.117)
Constant	10.08***	10.07***	10.08***	10.09***
	(0.0638)	(0.0644)	(0.0641)	(0.0659)
Shopping area fixed effects	Yes	Yes	Yes	Yes
Year-and-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	1,868	1,868	1,868	1,868

In column (3), we include "*Heat_level1*" dummy indicating whether the temperature between the 60th quantile and the 80th quantile or not, and "*Heat_level2*" dummy indicating whether the temperature exceeds the 80th quantile or not; Standard errors in parentheses are clustered by shopping area

*$p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

cubic for the other one). We observe a significant discontinuity with a large magnitude at the cutoff in both specifications (the first two columns in Table 4's Panel A). An incidence-rate ratio calculation indicates that restaurant visits (proxied by review counts) experience a 4 percent drop at the dirty day cutoff. For shopping area visits, there is also a discontinuity but the drop is statistically insignificant (column (4) in this Panel). The air purification system in shopping malls might help to alleviate the negative impact of severe pollution. This point bears repeating. Our regressions yield the effect of pollution net of any offsetting activities engaged in by the for-profit firms. If firms are aware that pollution lowers the demand for visiting their stores and restaurants, then they will have an incentive to invest in technology to offset the challenge. Small restaurants and stores will be less likely to invest in such costly technology.

Beijing Municipal Government's Emergency Office started to implement the pollution alert system at the end of 2013. If this Office forecasts an upcoming "heavy or severe" pollution event, it will issue an official alert 1 day in advance. During our study period for restaurant visits, roughly 26 percent of the real "dirty days" were successfully forecasted by this Office with such a pollution alert issued. If Beijing residents form their expectation on the basis of such alerts and engage in extra avoidance behavior (Sun et al., 2017), we would observe a larger drop in restaurant visits when such an alert is issued in advance. We test for such an anticipation effect by excluding the days with advanced alert in our restaurant RDD model (column (3) in Panel A).[13] The coefficient of "dirty day" dummy loses its significance, confirming that those "dirty days" featuring an advanced alert lead to much larger drops in visits because of the anticipation effect, and thus contribute to the significant discontinuity we observe in columns (a) and (b).

In Panel B and Panel C of Table 4, we present IV estimates. Existing studies show that cross-geographic area pollution flows offer such an IV for local pollution (Bayer, Keohane, & Timmins, 2009; Zheng et al., 2014). To create this cross-boundary spillover measure, we first define the "surrounding cities" as cities in the straight-line distance range of 100–200 kilometers to Beijing.[14] The industrial smoke emission in Beijing, which reflects the intensity of the industrial activity, is not significantly related to that in each of those surrounding cities.[15]

We divide Beijing restaurants into four quadrants on the basis of their addresses.[16] For each restaurant, we calculate the mean value of $PM_{2.5}$ concentration of the monitoring stations in the surrounding cities in the same quadrant (*NEIGHBOR*) on that day as the IV for the local $PM_{2.5}$ concentration this restaurant faces on the same day.

In the first stage, our IV (*NEIGHBOR*) has the expected sign and is also statistically significant in both restaurant and shopping area regressions, indicating that nearby cities' pollution does have a strong explanation power in Beijing's local pollution. In the second stage, the coefficient of our key variable ($PM_{2.5}$) is still statistically significant in both the restaurant and shopping area regressions. According to the IV regression results in column (2) of Panel B and Panel C, the restaurant visit and shopping area visit will decrease by 0.37 percent and 0.28 percent, respectively, if $PM_{2.5}$ concentration increases by 10 percent. These are larger in magnitude than our baseline estimates. One possible reason is that the local unobservables affect pollution and leisure activity in the same directions. Another possibility is that because the IV estimate is unaffected by the measurement error in the treatment variable, it tends to be larger than the baseline estimates (Becker, 2016).

We also explore other local sources of $PM_{2.5}$ in Beijing. The manufacturing activity is very low – most factories moved out before the 2008 Beijing Olympic Game. Besides the cross-boundary pollution inflow from nearby manufacturing cities, the other two major sources of local pollution are traffic congestion and coal-based heating.

[13]In our study period of shopping area visits, this office issued an alert for all "dirty days", so we are unable to conduct this test using the shopping mall data set.

[14]To avoid the high correlation of the industrial activity between the Beijing economy and its nearby neighbors, we exclude the very closeby cities within 100 km, such as Langfang (50 km). The surrounding cities include Tianjin (110 km), Tangshan (155 km), Baoding (140 km), Zhangjiakou (164 km), and Chengde (176 km).

[15]According to statistics (between 2010 and 2016), the correlation coefficients are ranged from −0.208 to 0.655, and the significance levels are ranged from 0.158 to 0.988.

[16]These four regions are the northeastern region, southeastern region, southwestern region, and northwestern region.

TABLE 4 RDD and IV estimates of the restaurant and shopping area regressions

Panel A. RDD estimates of the baseline regressions

	Restaurant regression			**Shopping area regression**
	(1)	**(2)**	**(3)**	**(4)**
Dependent variable	***Daily count***	***Daily count***	***Daily count***	**ln(*PM2.5*)**
Bandwidth	$h = 30\ \mu g/m^3$	$h = 50\ \mu g/m^3$	$h = 30\ \mu g/m^3$ (exclude days with an alert issued in advance)	$h = 30\ \mu g/m$
Dirty day	−0.0521***	−0.0372**	−0.0158	−0.0932
	(0.0177)	(0.0186)	(0.0181)	(0.0570)
Control variables	Yes	Yes	Yes	Yes
Polynomial of *M*	Quadratic	Cubic	Quadratic	Quadratic
Constant	Yes	Yes	Yes	Yes
Observations	449,357	802,656	431,228	160

Panel B. IV estimates on baseline restaurant regressions

Dependent variable	**(1)** **ln(*PM2.5*)** **First stage**	**(2)** ***Daily count*** **Second stage**	**(3)** ***Daily count*** **Second stage**	**(4)** ***Daily count*** **Second stage**	**(5)** ***Daily count*** **Second stage**
ln(*NEIGHBOR*)	0.735***				
	(0.00470)				
ln(*PM2.5*)		−0.0381*	−0.00461	−0.0144	
		(0.0217)	(0.0175)	(0.0200)	
ln(*PM2.5*)**Temperature*			−0.00301***		
			(0.000699)		
ln(*PM2.5*)**Heat_level1*				−0.105***	
				(0.0114)	
ln(*PM2.5*)**Heat_level2*				−0.0826***	
				(0.0149)	
(*PM2.5*)					−0.130**

(Continues)

TABLE 4 (Continued)

Panel B. IV estimates on baseline restaurant regressions					
	(1)	(2)	(3)	(4)	(5)
	ln(*PM2.5*)	*Daily count*	*Daily count*	*Daily count*	*Daily count*
Dependent variable	First stage	Second stage	Second stage	Second stage	Second stage
					(0.0521)
(*PM2.5*)^2					0.0259**
					(0.0125)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Observations	3,040,472	3,040,472	3,040,472	3,040,472	3,040,472
R-squared	0.515				
Panel C. IV estimates on baseline shopping area regressions					
	(1)	(2)	(3)	(4)	(5)
	ln(*PM2.5*)	*Daily visits*	*Daily visits*	*Daily visits*	*Daily visits*
Dependent variable	First stage	Second stage	Second stage	Second stage	Second stage
ln(*NEIGHBOR*)	1.073***				
	(0.0306)				
ln(*PM2.5*)		−0.0278***	0.0184**	−0.00697	
		(0.00686)	(0.00838)	(0.0123)	
ln(*PM2.5*)**Temperature*			−0.00373***		
			(0.000298)		
ln(*PM2.5*)**Heat_level1*				−0.0430***	
				(0.00435)	
ln(*PM2.5*)**Heat_level2*				−0.0680**	
				(0.0288)	
(*PM2.5*)					−0.0967***
					(0.0248)

(Continues)

TABLE 4 (Continued)

Panel C. IV estimates on baseline shopping area regressions					
	(1)	(2)	(3)	(4)	(5)
	ln(*PM2.5*)	*Daily visits*	*Daily visits*	*Daily visits*	*Daily visits*
Dependent variable	**First stage**	**Second stage**	**Second stage**	**Second stage**	**Second stage**
$(PM2.5)^2$					0.0244***
					(0.00729)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Observations	1,864	1,864	1,864	1,864	1,864
R-squared	0.665				

In the restaurant regressions, the control variables are temperature, wind speed, precipitation, district fixed effects, and year-and-quarter fixed effects, standard errors in parentheses are clustered by the restaurant. In the shopping area regressions, the control variables are temperature, wind speed, precipitation, district fixed effects, and year-and-quarter fixed effects, standard errors in parentheses are clustered by shopping area. In Panel B and Panel C, the first stage results of columns (3) to (5) are not shown, but they are consistent with the baseline results. “Dirty day” indicates the day's pollution level is “heavily polluted” or “severely polluted”, the $PM_{2.5}$ concentration on a “dirty day” is higher than 150 μg/m^3; the forcing variable M is measured as the difference between $PM2.5$ and the threshold, $M = PM2.5 – 150$ μg/m^3

*$p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

TABLE 5 Estimating the rebound effect of air pollution on leisure activity

Panel A. Restaurant regression			
Subsample: Bluesky days	**(1)**	**(2)**	**(3)**
Dependent variable:	***Daily count***	***Daily count***	***Daily count***
Number of consecutive dirty days before that day	0.0103***	0.0203***	0.00119
	(0.00186)	(0.00442)	(0.00233)
(*Number of consecutive dirty days before that day*)^2		−0.00233**	
		(0.000983)	
Number of consecutive extremely dirty days before that day			0.0517***
			(0.00798)
Control variables	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Observations	1,632,239	1,632,239	1,632,239
Panel B. Shopping area regression			
Subsample: Bluesky days	**(1)**	**(2)**	**(3)**
Dependent variable:	***Daily visits***	***Daily visits***	***Daily visits***
Number of consecutive dirty days before that day	0.000528	0.0166***	−0.00242
	(0.00176)	(0.00144)	(0.00189)
(*Number of consecutive dirty days before that day*)^2		−0.00268***	
		(0.000416)	
Number of consecutive extremely dirty days before that day			0.0187***
			(0.00232)
Control variables	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Observations	1,184	1,184	1,184

In the restaurant regressions, the control variables are temperature, wind speed, precipitation, district fixed effects, and year-and-quarter fixed effects, standard errors in parentheses are clustered by the restaurant. In the shopping area regressions, the control variables are temperature, wind speed, precipitation, district fixed effects, and year-and-quarter fixed effects, standard errors in parentheses are clustered by shopping area. "Blue sky" day indicates the day is rated as "excellent" or "good" in terms of air quality, "dirty day" indicates that the daily pollution level is "heavily polluted" or "severely polluted", "extremely dirty day" day indicates that the day's pollution level is "severely polluted".

*$p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

We collect the daily city-level traffic congestion index (*TCI*) from Beijing Transportation Research Center (under the Beijing Municipal Commission of Transport) and construct a dummy (*HEATING*) indicating whether a day is in the winter heating period (referring in particular to coal-based heating in Beijing). These two variables are not exogenous, but they help in understanding the various sources of Beijing's heavy air pollution. We include them in an additional two-stage regression in Table A4. The two local pollution sources both contribute significantly to Beijing's $PM_{2.5}$ concentration, and the second stage yields similar result as that in Table 4. We also include *TCI* and *HEATING* as control variables in our baseline regressions, and the main findings still hold.

Panel B and Panel C also report IV results for the regressions that include the interaction terms of temperature with two "heat level" dummies. Those interaction terms are all significantly negative with similar magnitudes as those in our baseline negative binomial regressions. The last column of each Panel presents the nonlinear effect of $PM_{2.5}$, and the nonlinear negative relationship holds for both samples up till the far-right

TABLE 6 Heterogeneous effects of pollution on the restaurant visit count

Panel A: high quality vs. low-quality restaurants				
Dependent variable: *Daily count*	**Overall score**	**Taste score**	**Environment score**	**Service score**
Bluesky (1 = Air quality is excellent or good)	−0.722***	−0.674***	−0.492***	−0.498***
	(0.0429)	(0.0462)	(0.0547)	(0.0566)
Bluesky × Score quartile bin dummies:				
Default: *Bluesky* × *Score* ∈ (0%, 25%]				
Bluesky × *Score* ∈ (25%, 50%]	0.534***	0.532***	0.259***	0.355***
	(0.0585)	(0.0604)	(0.0710)	(0.0741)
Bluesky × *Score* ∈ (50%, 75%]	0.793***	0.745***	0.691***	0.622***
	(0.0571)	(0.0652)	(0.0736)	(0.0768)
Bluesky × *Score* ∈ (75%, 100%]	1.248***	1.161***	0.878***	0.886***
	(0.0598)	(0.0620)	(0.0730)	(0.0740)
Control variables	YES	YES	YES	YES
Constant	YES	YES	YES	YES

Panel B: Restaurants with different cuisines and types			
Dependent variable: *Daily count*	**Cuisine**	**Group**	**Type**
Bluesky (1 = Air quality is excellent or good)	0.0425	*Bluesky* (1 = Air quality is excellent or good)	0.118***
	(0.0399)		(0.0121)
Bluesky × Cuisine dummies:		*Bluesky* × Type dummies:	
Default: *Bluesky* × *Cuisine_Foreign*		Default: *Bluesky* × *Type_NonFast*	
Bluesky × *Cuisine_Chinese*	0.128**	*Bluesky* × *Type_Fast*	−0.412***
	(0.0566)		(0.0666)
Bluesky × *Cuisine_Missing*	−0.269***	*Bluesky* × *Type_Missing*	−0.467***
	(0.0593)		(0.0846)
Control variables	YES	Control variables	YES
Constant	YES	*Constant*	YES

The control variables are temperature, wind speed, precipitation, district fixed effects, and year-and-quarter fixed effects; The standard errors in parentheses are clustered by shopping area and restaurant, respectively

*$p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

end of the $PM_{2.5}$ distribution. Compared with the linear IV estimates, the coefficients of *PM2.5* and $(PM2.5)^2$ are more significant.

3.4 | The rebound effect

Patient people engage in intertemporal substitution and delay their leisure trips to days featuring better air quality. This behavioral response will lead to a rebound effect, such as a spike in leisure activities on the first blue sky day after several consecutive polluted days. We test for this effect in Table 5 by only keeping blue sky days (air quality is “good” or “excellent”) in both the restaurant and shopping area samples. We count the number of consecutive “dirty days” before each blue-sky day, and examine whether consumers will make up for past lost leisure opportunities by going out more after multiple bad days. More than 90 percent blue sky days see no “dirty days” beforehand in our study period.

In column (a) of each Panel, we use the number of "dirty days" (highly or severely polluted) and the rebound effect is significant for restaurants but not for shopping areas. Considering that the effect might be nonlinear, we include the square of this number in column (b) of each Panel. The turning point in this U-shape is 4.4 and 3.1 consecutive "dirty days" for restaurants and shopping areas, respectively. In fact, less than 1 percent of blue sky days come after at least 5 consecutive "dirty days" in the restaurant sample; and less than 1 percent of blue sky days come after at least 4 consecutive "dirty days" in the shopping area sample. That is to say, this rebound effect increases at a diminishing rate with the number of consecutive dirty days in most cases. In column (c) we narrow down and only count the number of consecutive severely polluted days before a blue sky day. The rebound effect for both samples is quite large and significant – one additional "severely polluted" day is associated with a roughly 5 percent or 2 percent increase in restaurant or shopping area visit, respectively, on the following blue-sky day.[17]

To test whether yesterday's $PM_{2.5}$ concentration would have an impact on today's leisure activity, we augment the baseline model by adding the lag term of *PM2.5* in both shopping area and restaurant regressions (Table A2). No significant effect is found for restaurants or shopping areas.

3.5 | Heterogeneous effects of pollution on leisure activity

We examine the heterogeneous effects of air pollution on various types of restaurants. For each restaurant in our data set, we observe an indicator of its cuisine, quality and whether it offers fast food. In Panel A and Panel B of Table 6, we report new estimates of Equation (4) to test for the heterogeneous effects of pollution as a function of these variables. Such interactions allow us to test what types of restaurants gain more (holding prices constant) from a decline in ambient pollution. We divide the full sample into four groups, according to the quantile of various restaurant scores. In Panel A, we include the interaction terms between *PM2.5* and the score quantile bin dummies. The default group includes restaurants with the lowest scores. The results indicate a larger increase in visits for higher-quality restaurants during blue sky days. In particular, blue sky has a negative or little impact on visits to low-quality restaurants. This implies a substitution effect between higher-quality restaurants and low-quality restaurants. People may prefer to high-quality restaurants for better social interactions on blue sky days. Restaurants with higher scores attract higher-income customers, who are more responsive to air pollution.

In Panel B, we disaggregate the effects of air quality on different cuisine or types of restaurants. The results show that the visits of Chinese cuisine restaurants are higher under excellent or good air quality, compared with foreign cuisine restaurants. One possible explanation is that party dinners are more likely to occur on blue sky days and Chinese restaurants are preferred when large groups are dining. The impact of blue sky on fast food restaurant reviews is relatively small compared with restaurants serving table meals.

4 | CONCLUSION

Given the high level of air pollution in Beijing, China, it's air pollution dynamics offer the opportunity to test how the demand for the consumer city is affected by pollution. Using various data sets of Beijing in recent years, we document that air pollution reduces residents' restaurant visits (proxied by restaurant reviews) and shopping area visits. Such negative impact is larger in extreme weather conditions – when the temperature is high, blue sky days after multiple bad pollution days, and in response to advanced alert of dirty days. We also observe that clean air increases the demand for higher-quality restaurants to a larger extent than that for lower-quality restaurants.

We find that the population is responsive to government announcements. Controlling for the actual level of outdoor air pollution, government announcements of hazardous air reduce the demand for the consumer city.

[17]We acknowledge that the rebound effect on restaurant visits may be overestimated, because of the potential lag effect of reviews.

Patient people may delay their leisure trips to other days when air quality is better. Future research could explore other margins of adjustment to high levels of air pollution including take-out/delivery service dynamics.

In our past research, we have documented a complementarity between public investment in high-speed subways and Beijing new parks with private sector investment in nearby housing and the opening of new restaurants (Zheng & Kahn, 2013). In this paper, we document that there is also a complementarity between the demand for the consumer city and air pollution and climate conditions of that day.

This suggests that there may be a large consumer quality of life benefits enjoyed in Beijing if effective air quality regulation is enforced. Recent research has documented that China's pollution is forcing some residents to migrate abroad (Qin & Zhu, 2018). Effective environmental regulation is likely to affect Chinese urbanites' choices over where to live and how to plan out their day to day life choices. The net effect will be an increase in urbanites' standard of living as time outside and time with friends during consumption will be optimized without facing the "pollution tax".

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Appendix A

As the individual-level restaurant review count (*Daily count*) is an integer variable with a lot of zero values, we employ the zero-inflated negative binomial model in Table 2. In Table A1 below, we repeat those regressions by using the standard negative binomial estimator to check the robustness.

The results of the first three columns are quite similar to those in Table 2. In the last column, unlike the monotonically negative relationship between $PM_{2.5}$ concentration and visits we find in Table 2, the relationship here shows a U-shape. After checking the distribution of our restaurant-day observations, we find that more than 95 percent of the observations are on the left hand of the turning point, still indicating that in general, restaurant visits decline with rising pollution level.

We conduct some robustness checks of our baseline results in Table A2. We consider the reliability of $PM_{2.5}$ data. China's official daily reporting data of air quality (before 2011) has been questioned by some researchers. After the establishment of the station-level real-time air quality monitoring network, the government has a very little ability to manipulate $PM_{2.5}$ data. We replace the variable *PM2.5* with the $PM_{2.5}$ concentration data from the U.S. Embassy in the related regressions. Furthermore, we consider the impacts of Asia-Pacific Economic Cooperation (APEC) China 2014 on air quality and people's leisure activities. Beijing municipal government has implemented several emission control measures to greatly lower local air pollution level before and during APEC. The economic activities have also reduced because of the six-day vacation during the APEC China 2014. We drop the observations from November 1st to November 12th and re-run the baseline regression in the last column. Results in these columns are consistent with our baseline findings.

We further investigate the lagged effect of air pollution on leisure activity, with results reported in Table A3. The coefficient of lagged $PM_{2.5}$ is not significant in either shopping area regression or restaurant regression.

TABLE A1 Traditional negative binomial estimates of restaurant baseline regressions

Dependent variable: *Daily visits*	(1)	(2)	(3)	(4)
ln(*PM2.5*)	−0.00609NaN	0.0111NaN	0.00748NaN	
	(0.00149)	(0.00205)	(0.00162)	
ln(*PM2.5*)NaN*Temperature*		−0.00166NaN		
		(0.000152)		
ln(*PM2.5*)NaN*Heat_level1*			−0.0516NaN	
			(0.00490)	
ln(*PM2.5*)NaN*Heat_level2*			−0.0592NaN	
			(0.00427)	
PM2.5				−0.0267NaN
				(0.00453)
$(PM2.5)^2$				0.00482NaN
				(0.00137)
Control variables	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Observations	1,868	1,868	1,868	1,868

The control variables are temperature, wind speed, precipitation, district fixed effects, and year-and-quarter fixed effects. In column (3), we include "*Heat_level1*" dummy indicating whether the temperature between the 60th quantile and the 80th quantile or not, and "*Heat_level2*" dummy indicating whether the temperature exceeds the 80th quantile or not; Standard errors in parentheses are clustered by the restaurant;
$^{**}p < 0.05$
$^{*}p < 0.1.$
$^{***}p < 0.01.$

TABLE A2 Robustness checks for baseline regressions

Dependent variable	Restaurant regression		Shopping area regression
	Daily count	*Daily count*	*Daily visits*
	Full sample	**Exclude APEC period**	**Full sample**
	Full sample	Exclude APEC period	Full sample
ln(*PM2.5_US Embassy*)	−0.0197NaN		−0.0103NaN
	(0.00183)		(0.00342)
ln(*PM2.5*)		−0.0190NaN	
		(0.00191)	
Control variables	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Observations	3,070,244	3,086,278	1,744

Abbreviation: APEC, Asia-Pacific economic cooperation.
In the restaurant regression, the control variables are temperature, wind speed, precipitation, district fixed effects, and year-and-quarter fixed effects. The standard errors in parentheses are clustered by the restaurant; in the shopping area regression, the control variables are temperature, wind speed, precipitation, district fixed effects, and year-and-quarter fixed effects. The standard errors in parentheses are clustered by shopping area;
$^{**}p < 0.05$, $^{*}p < 0.1.$
$^{***}p < 0.01.$

TABLE A3 Lag effect of air pollution on leisure activity

Dependent variable	Restaurant regression *Daily count*	Shopping area regression *Daily visits*
ln($PM2.5_t$)	−0.00705***	−0.0146***
	(0.00137)	(0.00250)
ln($PM2.5_{t-1}$)	0.00171	0.00236
	(0.00130)	(0.00192)
Control variables	Yes	Yes
Constant	Yes	Yes
Observations	3,142,693	1,848

In the restaurant regression, the control variables are temperature, wind speed, precipitation, district fixed effects, and year-and-quarter fixed effects. The standard errors in parentheses are clustered by the restaurant; in the shopping area regression, the control variables are temperature, wind speed, precipitation, district fixed effects, and year-and-quarter fixed effects. The standard errors in parentheses are clustered by shopping area; **$p < 0.05$, *$p < 0.1$.
***$p < 0.01$.

In our IV analysis, we employ the $PM_{2.5}$ concentration in neighboring cities as the exogenous variation of Beijing's air pollution and construct our IV *NEIGHBOR*. We further consider other local sources of $PM_{2.5}$ pollution in Beijing. Before the Beijing 2008 Olympic Games, most of the highly-polluted industrial firms have been moved out of the city. Therefore, the local sources of pollution are mainly traffic vehicle emission and coal-based winter

TABLE A4 Additional two-stage restaurant regression results

Dependent variable	ln(*PM2.5*)	*Daily count*
	First stage	Second stage
ln(*NEIGHBOR*)	0.727NaN	
	(0.00471)	
TCI	0.742NaN	
	(0.00727)	
$(TCI)^2$	−0.860NaN	
	(0.00639)	
HEATING	0.0690NaN	
	(0.00126)	
ln(*PM2.5*)		−0.0351NaN
		(0.0213)
Control variables	Yes	Yes
Constant	Yes	Yes
First-stage IVs		*NEIGHBOR*, *TCI*, $(TCI)^2$, *HEATING*
Observations	3,016,007	3,016,007
R-squared	0.517	

Abbreviation: IV, instrumental variable.
There are some missing values in the *TCI* data. The control variables are temperature, wind speed, precipitation, district fixed effects, and year-and-quarter fixed effects. The standard errors in parentheses are clustered by the restaurant;
**$p < 0.05$
*$p < 0.1$.
***$p < 0.01$.

heating. In Table A3, we include two additional variables in the first stage to control for these two sources. The daily *TCI* is the aggregate measure of motorized traffic flow, with 0 referring to no congestion at all and 1 referring to complete gridlock. This *TCI* data is not available after 2015, therefore we only analyze the restaurant visits in Table A4. According to Beijing's winter heating schedule, we conduct a dummy *HEATING* indicating whether the day is in the coal-based heating period or not. The results show the inverted-U relationship between *PM2.5* and *TCI*, which is consistent with the finding of Sun et al. (2014). The positive correlation between *PM2.5* and *HEATING* is also found in the results. As *TCI* and *HEATING* are not exogenous, we acknowledge that this two-stage estimate is not a valid IV estimate, but it provides additional evidence supporting our baseline findings.