Behavioral and Distributional Implications of Air Pollution Information on Urbanites' Outdoor Physical Exercise

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Abstract

Governments usually advise citizens to reduce outdoor physical activities when ambient air pollution is high through publicizing the air quality index (AQI) and pollution avoidance guidance. Despite the wide adoption of such information policy worldwide, there is limited causal evidence of how urbanites' engagement in outdoor exercise changes in response to air pollution, as well as the distributional impacts across socio-economic groups. Here, we built a unique panel dataset using 30 million outdoor exercise records from a smartphone app to track exercise activities of people all over China. Employing an instrumental variable approach, we show that a 10 μg/m^3 increase in ambient PM2.5 concentration reduces the proportion of people doing outdoor exercise by 1.43%. We find a discontinuous reduction in outdoor exercise when ambient pollution level surpasses the "heavy pollution" threshold, suggesting that people are responsive to public pollution guidance. Further analysis of heterogeneity shows that individuals in well-educated neighborhoods are more likely to reduce outdoor exercise when the ambient air pollution level is high than people in low-education neighbourhoods. Such avoidance disparity is enlarged when pollution alerts are issued. We find suggestive evidence that asymmetric subjective perception of pollution severity and health impacts, rather than access to objective pollution information, is the key mechanism driving avoidance disparity. These findings illustrate that information failure exists even when governments supply real-time pollution information to all. The environmental inequality caused by awareness constraints of less educated urbanites should be integrated into policy considerations when balancing between public mitigation and private avoidance efforts.

Key Words: air pollution, avoidance behavior, information policy, physical activity, China

Introduction

Air pollution is one of the most significant public health hazards worldwide. Concurrent with rapid urbanization, 92% of the global population experiences poor air quality (Kirby, 2016), causing nine million premature deaths and resulting in a significant amount of respiratory and cardiovascular diseases each year (Manisalidis et al., 2020). Air pollution also increases infant mortality (Heft-Neal et al., 2018; Tanaka, 2015), reduces labor supply and productivity (T. Chang et al., 2016; T. Y. Chang et al., 2019; J. He et al., 2019), and affects psychological well-being (Xue et al., 2019; Zhang et al., 2017; Zheng et al., 2019). Because of the growing public concerns for air pollution, jurisdictions worldwide have implemented information programs, providing air quality indices and pollution alerts to the mass public (Barwick et al., 2019; H. Chen et al., 2018; Neidell, 2010). The point of such information programs is to advise the public to take up voluntary pollution avoidance behaviors in a timely manner, which is touted as the new wave of low-cost environmental regulation (Graff Zivin & Neidell, 2009). Such information policy is popular in developing countries due to the difficulty of cleaning up the air while preserving economic development; as well as in many developed countries like the US and Australia where climate change is causing increased frequency of wildfire-induced hazardous pollution events.

Given the importance of pollution information programs, empirical evidence on their effectiveness remains scarce. Previous research used quasi-experimental designs and documented revealed market behaviors of defensive equipment purchasing on highly polluted days, such as face masks and air purifiers (Ito & Zhang, 2020; C. Sun et al., 2017). Pollution information and alerts also increase inter-city travel (Cui et al., 2019), reduce the usage of public bikes (Saberian et al., 2017), reduce restaurant visitations (C. Sun et al., 2019), and decrease the visitation to outdoor recreational locations like Los Angeles Zoo, the Griffith Observatory (Graff Zivin & Neidell, 2009), Bristol Zoo (Janke, 2014), and US national parks (Keiser et al., 2018). Although outdoor physical exercise under heavy pollution has the largest health impacts due to increased inhalation rate (Stieb et al., 2017) and is the central element in public pollution avoidance guidance, no study to date has provided causal evidence of air pollution information on outdoor exercise. Besides, most of the existing evidence above rely on location-based rather than individual-based panel data, making it difficult to control for population compositional effects or infer socio-demographic differences in avoidance behaviors. Understanding the behavioral response in outdoor exercise and its distributional consequences is crucial for quantifying the benefits of information policy and for tailoring interventions to specific subgroups.

Here we report on the effect of ambient air pollution on participation in recreational physical exercise, using a unique panel dataset from a smartphone app covering millions of people all over China. China is an ideal setting to test the effect of pollution information as the pollution disclosure system is well-developed (Barwick et al., 2019) and the frequency of heavy pollution events is much higher than in Western countries (Rohde & Muller, 2015). Meanwhile, due to the embracement of Internet-of-things (IoT), 87% of urbanites in China with mobile phones are using smartphones with 4G connectivity, among the highest in the world (Deloitte, 2016). Smartphone data enables researchers and policymakers to track human behaviors with high spatial and temporal granularity, circumventing the limited sample and self-reporting biases in traditional survey data.

There are two key findings in this paper. First, we develop robust causal estimates of the impact of air pollution on outdoor physical exercise. We build an instrumental variable based on daily variation in wind directions and air pollution levels of upwind cities and run two-stage-least-square analysis. We show that a 10 $\mu g/m^3$ increase in ambient PM2.5 concentration reduces the proportion of people doing outdoor exercise by 1.43%. We find limited evidence supporting behavior adjustments on the intensive margins (i.e., reducing exercise time or substituting to indoor exercises). In addition, we use a regression discontinuity design to test threshold effects and find that people respond to air quality index discontinuous around the "heavy pollution" threshold, suggesting that public pollution information plays a role in guiding avoidance behaviors.

Second, we find that awareness of pollution health impacts can cause large disparities in avoidance behavior across socio-economic groups, even when access to objective pollution information is available to all. Previous literature usually focuses on the supply of pollution information (Barwick et al., 2019; Gao et al., 2021; Ito & Zhang, 2020) to explore the consequences of information asymmetry. We show that people in higher education neighbourhoods have much steeper response elasticity to ambient air pollution in reducing outdoor exercise even when pollution information is available to all. Such disparities grow rather than narrow when city governments issue air pollution alerts in advance. Further results from a large-scale survey from a polluted city in the middle of China show that individual's perceptions of the severity of local air pollution and its health impacts significantly increase with education, even for people within the same city and thus facing identical local air pollution.

This study provides three primary contributions to the existing literature. First, it adds to the literature of pollution avoidance behavior by providing the first large-scale causal evaluation of how urbanites' outdoor physical exercise responds to information on ambient air pollution. Research linking air pollution information and physical activity primarily relied on self-reported cross-sectional surveys (R. An & Xiang, 2015); (Wen et al., 2009). They either find people in more polluted areas exercise less (Roberts et al., 2014; Wen et al., 2009) or document that people reported exercise less if air quality is bad (Wells et al., 2012). A caveat of survey evidence is that self-reported survey data are susceptible to memory errors and social desirability bias (Adams et al., 2005; Hu et al., 2017) and cannot reflect behavioral response in a natural context[1]. Besides, the cross-sectional data structure makes the results susceptible to selection bias and omitted variable biases (Ruopeng An et al., 2019) (e.g., exercise-lovers who will exercise more anyway might select into cleaner cities). The physical exercise dataset used in this study is high granular panel data, which allows us to control for high dimensional temporal and individual fixed effects, and to use quasi-experimental designs to develop causal estimates.

Second, this study relates to the emerging literature of environmental inequality by showing how homogeneous public information can create disproportionate impacts in private behavioral response. People of lower socio-economic status suffered more from air pollution related mortality and morbidity (Fan et al., 2020; G. He et al., 2020). Previous literature mainly focuses on the location-driven pollution exposure inequality (Hajat et al., 2015) caused by residential sorting (H. S. Banzhaf & Walsh, 2008; Chay & Greenstone, 2005; Hausman & Stolper, 2020) and direct discrimination (S. Banzhaf et al., 2019). For behavior-driven inequality, literature mainly focuses on the revealed market behavior such as purchasing defensive equipment (Ito & Zhang, 2020; C. Sun et al., 2017). Unlike a perfect market, pollution avoidance behaviors rely critically on access to accurate pollution information and people's awareness of pollution health impacts (Greenstone & Jack, 2015). Inequality driven by hidden information has been tested empirically (Gao et al., 2021; Hausman & Stolper, 2020), yet how different knowledge and awareness can create exposure inequality given the same information supply has not received much attention. The findings of this research fill in this gap by providing empirical evidence on the role of awareness in creating pollution avoidance inequality in people's day-to-day non-market activities.

Finally, as physical exercise itself is an important health behavior, this research also connects with the literature on the pollution's health impacts by adding an indirect pathway of pollution on health through avoidance behaviors. Though abundant epidemiological research studies how direct exposure to pollutants contributes to mortality and morbidity, we know much less about how air pollution alters other human health behaviors. Recent discoveries have shown significant correlations between air pollution and exposure-irrelevant diseases like obesity, diabetes (Deschenes et al., 2020; Esposito et al., 2016; Guo et al., 2020; Liang et al., 2019) and depression (Wang et al., 2019), and hypothesize that reducing physical activity is one of the core behavioral channels (Deschenes et al., 2020; Wang et al., 2019). These facts combined suggest that changes in an active lifestyle can constitute a significant mediator between air pollution and its adverse health effects, and this paper provides quantitative evidence to advance our understanding on this important behavior channel.

[1] For example, people might not pay attention to air pollution information in their day-to-day life. Measuring people's exercise intention given a pollution scenario is likely to be very different from how people actually behave in real-life.

Background and Data

Research Context

In China, the real-time pollution monitoring and disclosure program started in 2013, marking a watershed moment in China's environmental regulations (Barwick et al., 2019). Although the daily Air Pollution Index (API) was published for major cities since 2000 from the Ministry of Environmental Protection (MEP), the pollution levels were reported by local governments and were found to have widespread manipulations (Ghanem & Zhang, 2014). Before the pollution monitoring and disclosure program established in 2013, the public could not distinguish between smog, fog, and air pollution. There were few discussions about air pollution in the mass media (Barwick et al., 2019).

Pollution information in China is released as the Air Quality Index (AQI), a synthesized index for all air pollutants ranging from 0 to 500. The AQI level has six groups according to the "*Ambient Air Quality Standards*" (GB 3095-2012) published by MEP (Table 1). AQI reflects the severity of the primary air pollution at each hour, among PM2.5, PM10, O3, NOx, and SO2. In the online pollution disclosure platform, the pollution index is color-coded by its category (from green to dark red) to signal the severity of air pollution. As can be seen, the official recommendation for pollution avoidance is centering around outdoor activity. The guidance is more qualitative, e.g., "properly reduce" and "reduce", which leaves discretion in the way people interpret such information and behave accordingly. To what extent does the mass public reduce outdoor physical exercise under different air pollution levels and recommendations relies heavily on the individual awareness of pollution health impacts.

Table 1. Air quality information disclosure and recommendation in China.

AQI range	Category	Suggestions
0-50	Excellent	All people can do activities normally.
51-100	Good	Very few sensitive populations should reduce outdoor activities.
101-150	Light pollution	Children, the elderly, and people with cardiovascular or respiratory diseases should reduce durable and high-intensity outdoor exercise.
151-200	Medium pollution	Children, the elderly, and people with cardiovascular or respiratory diseases should reduce durable and high-intensity outdoor exercise; The normal population should properly reduce outdoor exercise.
201-300	Heavy pollution	Children, the elderly, and people with cardiovascular or respiratory diseases should stop outdoor exercise; The normal population should reduce outdoor exercise.

> 300	Severe pollution	Children, the elderly, and people with cardiovascular or respiratory diseases should stay indoors and avoid physical exertion; The normal population should avoid outdoor activities.

Source: Official air quality information system published by China National Environmental Monitoring Center (http://www.cnemc.cn/).

Data

This study's primary data are exercise records from KEEP (https://www.gotokeep.com/), the most popular exercise app in China, from 2017-01-01 to 2017-12-31. All the exercise records used for this research are shared by users on their app social platform and can be publicly viewed. Unlike most physical activity datasets, KEEP exercise records track individuals over time. It has rich individual characteristics, including registration location (i.e., city and district), age, gender, weight, exercise history (i.e., total historical posts and joining date), social network (i.e., following whom and who follows them). Besides, KEEP exercise data also provides detailed information about each record's exercise type, categorized into five broad categories: normal (home or gym-based), run, cycling, hiking, yoga. The normal class refers to the exercise for which the app provides video instructions. These are usually indoor exercises such as weight training, dance, aerobics, and treadmill. For outdoor exercise, the approximate longitude and latitude of the starting point are available, and the distribution of geotagged outdoor exercise distribution across cities is displayed in Supplementary Figure 1.

Beyond the physical activity datasets, we collected hourly air pollution data from the 1,500 official pollution monitoring stations in China, including AQI, PM2.5, and O3. We aggregate the pollution data to city-date level by averaging across stations and across all the hours in the daytime (i.e., from 6 AM to 10 PM). Since weather is a crucial confounder affecting both pollution levels and outdoor activities, we also gathered meteorological data from 2,000 national meteorological monitoring stations as controls. Weather variables comprehensively include temperature, precipitation, relative humidity, wind speed, wind direction, and air pressure. Since sunny or cloudy is an important time-variant determinant for outdoor activities, cloud coverage data is collected from MERRA-2, M2T1NXRAD project (https://disc.gsfc.nasa.gov/datasets/M2T1NXRAD_V5.12.4/summary) to reduce the biases created through weather conditions. The spatial distribution of the monitoring stations is displayed in Supplementary Figure 2.

Finally, we compiled a socio-demographic dataset to support the heterogeneity analysis. City and district-level attributes related to socio-economic conditions are collected from the 2019 China City Statistical Yearbook and the 2010 Census of China, including per capita GDP, education rate, unemployment rate, etc. As research has documented tight positive correlation between housing price and income at household level (Määttänen & Terviö, 2014), we also collected the detailed neighbourhood level housing price data from one of the largest real estate transaction platforms Lianjia (https://m.lianjia.com/) as a proxy for household income (Supplementary Figure 4). We transformed point-level price data for each Xiaoqu (i.e., the smallest community unit in China) and rasterized the housing price to grid data with 3 km × 3 km spatial granularity (i.e., similar to the minimum size of census block in the US). Then we matched each exerciser's custom exercise location to the housing price grid to get the unit housing price of each resident's location and used it as a proxy for income. We also gathered the Point-of-interests (POIs) for each city which allows for estimating the proximity to exercise facilities like parks and gyms, allowing for the identification of place-determinants in the relationship between pollution and exercise.

Summary Statistics

We removed the users who were not in mainland China or solely used the exercise app for indoor exercise. We also collected the approximate geotagged location of each user's custom exercise places and removed the users whose registration cities do not match their custom exercise cities. This effort is made to ensure that the pollution level assigned to each user is accurately reflecting his surrounding environment. Table 2 presents summary statistics for the estimation sample. More than 200,000 users are remaining in our final dataset. The average age is 30 years old; female users comprise 55 percent; the average weight is about 64 kilograms. The exercise dataset used for regression consists of more than 22 million individual-day observations. The average daily concentration of PM2.5 is 42 μg/m^3, and the average synthesized air quality index (AQI) is 70. Figure 2 displays the general relationship between ambient PM2.5 concentration and the share of people doing outdoor exercise, which shows an apparent negative correlation.

Table 2. Summary statistics.

	Mean	Standard deviation	Min	Max	Observations
User					
Age	29.88	7.28	10	80	214,177
Gender (Female=1)	0.55	0.50	0	1	244,257
Weight (kg)	64.32	13.41	35	150	243,331
Neighbourhood Education (years)	10.09	1.71	0	15.37	141,128
Neighbourhood Housing Wealth (kRMB)	2,328.62	1,755.45	165.40	16,643.40	100,619
Exercise					
Air Quality Index (AQI)	69.86	41.50	10.29	500	31,110,400
PM 2.5 ($\mu g/m^3$)	42.20	33.95	1.33	1,719.61	31,110,044
Temperature ($^\circ C$)	20.13	9.38	–25.76	37.29	22,437,516
Doing outdoor exercise (binary)	0.16	0.37	0	1	31,113,226
Outdoor exercise duration (minute)	42.52	26.75	1	179.98	5,012,784

Notes: Table reports unweighted statistics for exercise app users with average exercise frequency above once per month in 2017. Exercise records are aggregated to individual-date level.

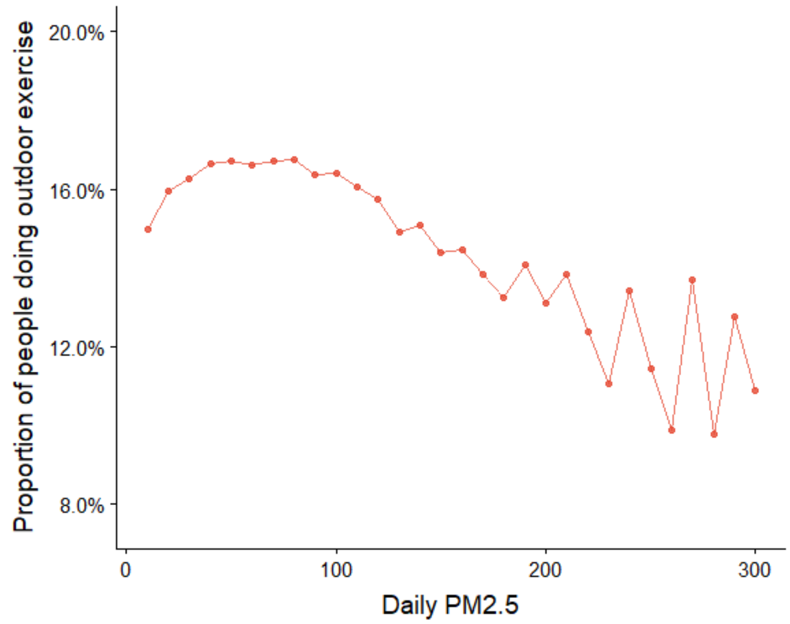


Figure 2. Correlation between PM2.5 and outdoor exercise rate.

Method

Marginal effects of ambient air pollution on physical exercise
The first objective of this study is to estimate the short-run impact of air pollution on the share of the population engaging in outdoor physical exercise. We model this relationship using the following fixed-effect regression model:

$$Y_{ict} = \beta POL_{ct} + X_{ct}\gamma + \delta_i + \theta_{dow} + \mu_{cm} + \varepsilon_{ict} \quad (1)$$

Where *i* indexes individual, *c* indexes the city, *t* indexes date. The outcome variable of interest Y_{ict} is a dummy variable measuring whether individual *has conducted* any outdoor exercise on date *t*. $POL_{ct}$is the average air pollution (either AQI or PM2.5 concentration) in city *c* on date *t*. Control variableX_{ct} includes weather controls (i.e., temperature, temperature^2, precipitation, wind speed, humidity, air pressure, and cloud coverage) and holiday dummy indicators. Taking advantage of the panel data structure, we include individual fixed effects (δ_i), day-of-week fixed effects (θ_{dow}), and city-by-month fixed effects (μ_{cm}) to reduce omitted variables. By controlling for individual fixed effects, we are essentially comparing the activity pattern of the same individual on polluted and non-polluted days, holding weather conditions. This approach largely alleviates the selection bias that people who have an innate preference for exercise tend to move to a cleaner city for living. The standard errors are clustered at the city level to non-parametrically adjust for arbitrary within-unit autocorrelation in the disturbance term ε_{ict}.

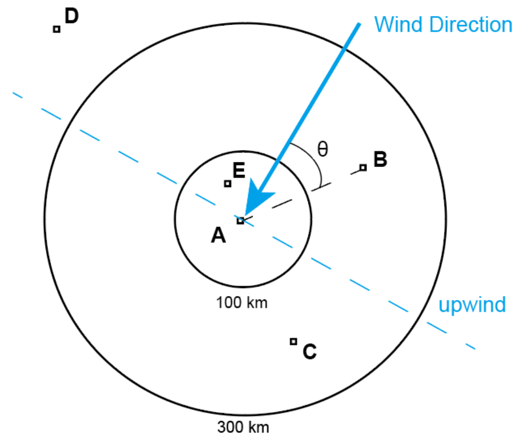
The identification challenge in this context is that local air pollution is usually endogenous to local activities. Though the reverse causality linkage between outdoor exercise and air pollution is arguably weak, we cannot completely rule out this possibility. For instance, suppose people use active commuting as outdoor exercise. On days people choose to commute by automobiles, the reduced outdoor exercise will increase local air pollution. To further mitigate such biases, we employ imported pollution from upwind cities to instrument local air pollution in the city of interest. The approach of constructing instruments is in a spirit similar to the source-receptor matrix built by the US EPA for air pollution prediction. We build a model to predict the air pollution level of a city based on pollution level and wind speed in other cities and divided by the distance between the two cities. Specifically, we instrument the POL_{ct} variable in (1) by $Pollution_{ct}^{up}$ computed using the following formula:

$$Pollution_{ct}^{up} = \sum_j max(cos\,\theta_{cjt}, 0) \times \frac{Pollution_{jt} \times WS_{jt}}{Distance_{cj}} \tag{2}$$

$$100\ km < Distance_{cj} < 300\ km$$

θ_{cjt} indicates the angle between the wind direction and the line connecting each city pair (see Figure 3 for illustration). Thus the $max(cos\,\theta_{cjt}, 0)$ term makes sure that only upwind cities are considered, and cities right in the wind direction are given higher weights (e.g., city C in Figure 3 will have zero contribution to the IV for city A).

The Monotonicity Assumption for IV naturally holds here as the imported pollution blown from upwind cities should increase local air pollution levels. We removed cities beyond 300 km away (e.g., city D in Figure 3) as air pollution from cities far away is unlikely to travel long distances, thus violating the Relevance Assumption. Furthermore, the Exclusion Restriction Assumption requires that pollution levels in upwind cities only affect local physical exercise through increasing local air pollution. As cities close to each other tend to have agglomeration in economic or industry activities leading to correlated endogenous factors, we further removed cities within 100 km to the city of interest (e.g., city E in Figure 3). One might also have concerns about the wind speed correlation across cities. As we only consider cities of distance and control for local wind speed in the main regression, the correlation in wind speed is unlikely to cause violations of the exclusion restriction. Many previous studies have adopted similar identification strategies (Bayer et al., 2009; S. Chen et al., 2021; Keiser et al., 2018; Zheng et al., 2019).



Heterogeneity

Since the average effect might mask substantial heterogeneity, we use subgroup analysis to explore the differential impacts of air pollution across subpopulations, which essentially include running the primary regression model for different subgroups separately and comparing their response coefficients. We decompose individuals into sub-groups with different ages, genders, weights, neighbourhood housing prices, and district education levels to explore individuals with which types of characteristics are more sensitive to air pollution in adjusting exercise behaviors.

Nonlinearity and threshold effects

The linear model assumes constant semi-elasticity in the response function, which might not be the case as responses could be steeper under heavy and severe pollution conditions than low pollution levels. We use the binned regression design to allow for nonlinear responses, by replacing the continuous pollution measurement of Equation (1) into categorical dummy indicators referring to each pollution level (excellent air quality is used as the baseline category):

$$Y_{ict} = \beta_1 Good_{ct} + \beta_2 LightPol_{ct} + \beta_3 MediumPol_{ct} + \beta_4 HeavyPol_{ct} + \beta_5 SeverePol_{ct} + X_{ct}\gamma + \delta_i + \theta_{dow} + \mu_{cm} + \varepsilon_{ict} \qquad (3)$$

To understand how behaviors are driven by public pollution disclosure and recommendation, we use binned regression coupled with a Regression Discontinuity Design (RDD) design to model the effect of the categorical pollution information guidelines displayed in Table 1.

The former analyses cannot distinguish whether people are responding to visibility or public pollution information. To test whether the pollution disclosure program plays a causal role, we exploit the fact that air quality categories and guidelines change discontinuously at the administratively defined thresholds of AQI. Since most pollution information platforms color-code the pollution category and display tailored guidelines, the changes in the pollution categories can stimulate a "jump" in outdoor physical exercise rate. We adopt the Regression Discontinuity Design (RDD) to test whether there are discontinuous changes at the thresholds. There might be omitted variables that simultaneously affect local air pollution and citizens' physical activity. However, when we narrow our focus to the hours with the pollution level right above and below the pollution category divisions, it becomes more plausible that pollution can be judged as locally randomized.

Here, the running variable is the daily average AQI. The treatment effect of air pollution information disclosure is determined by the discontinuous change in the physical exercise around the threshold for heavy pollution (i.e., AQI above 200). A challenge is that we do not know in which hours people pay attention to the pollution information; thus, daily average AQI might not accurately represent the real-time AQI when people search for it. We therefore adopt a "donut RDD" design (Barreca et al., 2011) by removing a buffer range of 10 in the air pollution index and detecting whether daily outdoor activity level significantly decreases from below 190 to above 210. The rationale is that due to high correlations in pollution index within a day[2], a day with average AQI above 210 is more likely to have many hours in the day above the heavy pollution threshold and vice versa. The "donut" approach can reduce the measurement errors in close proximity to the 200 threshold. The baseline analysis estimates the following regression within a narrow window determined by data-driven optimal bandwidth (Imbens & Kalyanaraman, 2011) around each pollution category threshold (about 30):

$$Y_{ct} = \alpha_0 + \alpha_1 POLcate_{ct} + \alpha_2 POLcate_{ct} \times f(dAQI_{ct}) + \alpha_3 (1 - POLcate_{ct}) \times f(dAQI_{ct}) + \varepsilon_{ct} \quad (4)$$

Where Y_{ct} is the residual from regressing the proportion of people doing exercise in city *i* at time *t* on daily weather conditions (the same as included in Eq.1), holiday controls, city fixed effects, month fixed effects and day-of-week fixed effects. $POLcate_{ct}$ is an indicator which equals 1 if at time *t* the AQI level is above the threshold for a specific pollution category. And $dAQI_{ct}$ is the distance of AQI to the threshold. The main focus of the analysis is for the medium and heavy pollution thresholds (i.e., AQI thresholds of 150 and 200). And we run similar regression using placebo thresholds ranging from 150 to 250 as placebo tests. The RDD polynomial *f*(.) is estimated separately on either side of the threshold. The baseline specification uses the local linear regression, as recommended by other papers of RDD applications (Anderson, 2014; Porter, 2003; A. Sun & Zhao, 2016), and a triangular kernel which gives higher weights to observations closer to the threshold. MSE-optimal bandwidths are used based on (Calonico et al., 2014). Results using different donut ranges and kernels are tested as robustness checks.

[2] Night-time between 10 PM and 6 AM is removed as the pollution level is usually quite different at night and it does not affect human activities.

Results

Marginal effect of air pollution on outdoor exercise

We first examine the relationship between concurrent PM2.5 and an individual's outdoor exercise behavior. The main analysis employs Equation (1) and has dummy variables indicating exercise or not as the major outcome. We adjusted the regression coefficient to measure the percent change in outdoor exercise rate by dividing the estimate by baseline exercise rate. The large first-stage F-statistics of two-stage-least-square (2SLS) analysis displayed in Columns (2) and (4) of Table 3 ensure that pollutants blown from upwind cities can serve as a strong instrument for local air pollution. The regression results show that air pollution significantly decreases outdoor exercise rate, both under OLS regression and 2SLS analysis (Column 1-2 in Table 3 shows the marginal effects of AQI, and Column 3-4 shows those for PM2.5). On average, a 10 $\mu g/m^3$ increase in concurrent PM2.5 is associated with a 1.43% (95% CI: 1.21%-1.65%) decrease in outdoor exercise rate under 2SLS regression. To put this into perspective, a 150 $\mu g/m^3$ increase in pollution level, which causes the air quality level from excellent to heavy pollution, led to a 21.5% decrease in daily exercise rate.

To further understand the behavioral pattern, we then investigate the changes taking place on the intensive margin. Specifically, we explore whether people adjust to air pollution by reducing exercise time instead of giving up exercise directly. The results show that people did reduce exercise time, yet the magnitude of change is very minimal (Supplementary Table 1). In addition, we find no evidence that people are substituting to indoor exercise (Supplementary Table 2). These results suggest that people mainly respond to heavy pollution by not exercising at all, instead of exercising for a shorter time or switching locations.

Table 3. The marginal effect of ambient air pollution on outdoor exercise rate.

	Outdoor exercise rate (percentage change)			
	(OLS)	(2SLS)	(OLS)	(2SLS)
	(1)	(2)	(3)	(4)
AQI	-0.0853***			
	(0.0198)			
PM2.5			-0.0944***	
			(0.0231)	
AQI IV		-0.1352***		
		(0.0079)		
PM2.5 IV				-0.1427***
				(0.0112)
dependent variable mean	16.11	16.11	16.11	16.11
First stage F-stats		36.8038		37.7163
weather controls	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
day-of-week FE	Yes	Yes	Yes	Yes
city-by-month FE	Yes	Yes	Yes	Yes
Observations	22,403,028	19,685,468	22,402,671	19,679,902
Adjusted R^2	0.1182	0.1191	0.1182	0.1190

Notes: *p<0.01; **p<0.005; ***p<0.001. Column 1-4 display the percentage change in outdoor exercise rate in response to a marginal increase in ambient air pollution. The original regression has a dummy variable indicating whether an individual exercises or not. The coefficients are adjusted to percentage change by dividing the average exercise rate within our sample year. Both OLS and 2SLS regression results are presented. Standard errors are clustered at the city level and shown in the parenthesis.

Nonlinearity and threshold effects

As human behaviors are responsive to their perceived pollution severity given public information, we expect nonlinearity in behavioral response by two primary sources. The first source of nonlinearity generates from the nonlinear health impacts of pollution exposure (Barwick et al., 2018). Intuitively, people are thus more likely to adjust behaviors when the ambient AQI rises from 175 to 200, compared with 25 to 50. The second source of nonlinearity originates from categorical air pollution information and guidelines published by the government (see Table 1 and the Background section). If people follow the public pollution guidelines, we would also expect the behavioral responses to be stronger under heavy pollution situations.

To explore the potentially nonlinear function form of the relationship between pollution and exercise, we first include higher-order polynomials of air pollution and corresponding IV in our main regression. Since higher-order terms are difficult to interpret, we plot the predicted marginal effects of the pollutant on outdoor exercise rate as a function of the air pollution (i.e., plotting the dose-response function). Such methods are widely adopted to estimate the nonlinearity of air pollution (Barwick et al., 2018; Schlenker & Walker, 2016). The dashed lines in Figure 4a show results from the linear dose-response model (i.e., constant marginal effect), while the solid line represents results from a quadratic model. The results suggest that the predicted marginal effect of air pollution increases with pollution level, meaning that people are becoming more sensitive to marginal increases in air pollution under high pollution situations.

To further consider the responses to categorical pollution information and alerts, we show the results of binned regression based on Equation (4) in Figure 4b. The behavioral responses are much steeper after the pollution level passes the medium pollution. Compared with days with excellent air quality, medium, heavy, and severe air pollution reduces outdoor exercise rate by 10.2%, 16.5%, and 34.7%, respectively. To put the results into perspective, a day with an average temperature above 30 °C and 35 °C depresses outdoor physical exercise by 5.0% and 18.1% (Supplementary Figure 5), indicating that the magnitude of physical exercise reduction caused by heavy air pollution is similar to or even beyond the effect of extremely hot days.

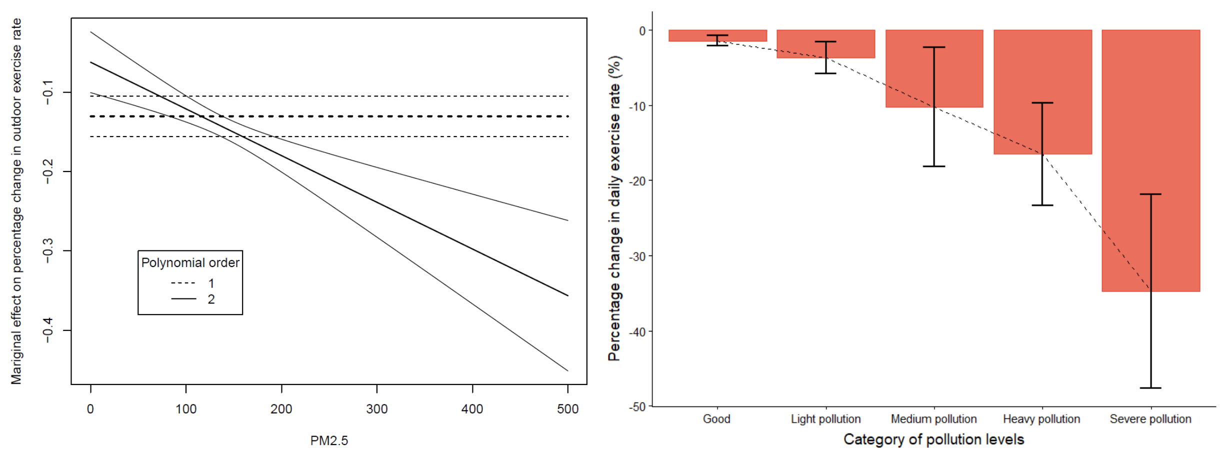


Figure 4. Nonlinear responses to air pollution. **a,** marginal effect of air pollution on outdoor exercise rate under linear and quadratic dose-response function (based on 2SLS regression). Dashed lines are estimates, and 95% confidence intervals for linear response and solid lines are those for quadratic response function. **b,** binned air pollution and outdoor exercise rate (based on OLS regression as the IV is not suitable for categorical air pollution). Excellent air quality is the baseline. Bars display the point estimates, and error bars show 95% confidence intervals.

As days with heavy air pollution usually have less visibility. Steeper behavioral responses might be the results of pollution visibility rather than public pollution information. To test whether the categorical pollution information and guidelines play a role, we explore whether the behavioral response pattern displays discontinuity at the government-set threshold of heavy air pollution (see Method). Figure 5 shows that the outdoor exercise rate significantly decreases when the daily average AQI passes the heavily polluted threshold (i.e., 200). When testing other pollution thresholds for placebo tests, the discontinuity is the largest around the heavy pollution threshold (AQI 200) and statistically insignificant around other AQI levels (Figure 5b). The significant discontinuity around AQI 200 is robust when changing the excluded range around the threshold to account for daily-level measurement error or the kernel used to run the analysis (see

Supplementary Table 3). These results combined suggest that the categorical pollution information issued by the central government did play a meaningful role in the alterations of physical exercise on polluted days.

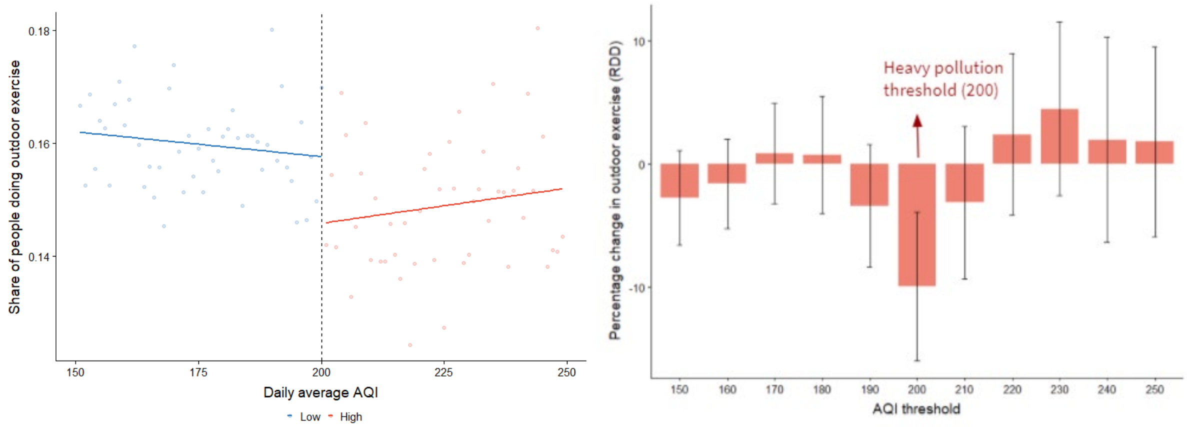


Figure 5. Regression discontinuity at the government-set heavy pollution threshold. **a,** Visual illustration of donut discontinuity around the heavy pollution threshold. We have partialled out daily weather conditions (the same as included in Eq.1), holiday controls, city fixed effects, month fixed effects and day-of-week fixed effects and obtained the residuals. **b,** Donut RDD regression coefficients with different pollution levels as thresholds.

Distributional effect

The above estimates represent an average effect of air pollution on outdoor physical exercise across all individuals within the dataset. However, we might expect heterogeneous responses as people with different socio-demographics might have different awareness of pollution avoidance and different exercise habits. For example, previous literature suggests that females are more sensitive to air pollution as shown by a larger reduction in subjective well-beings on polluted days (Zheng et al., 2019); elder people have higher risks of morbidity and mortality associated with pollution exposure (Peled, 2011); individuals with higher BMI have different sensitivity to the ambient environment in changing exercise pattern (Obradovich & Fowler, 2017); and income inequality widely exists in pollution avoidance behaviors (Ito & Zhang, 2020; C. Sun et al., 2017).

Figure 6 displays the results from subgroup analysis using the aforementioned dimensions of socio-demographic factors. As we lack access to height data, BMI is proxied using weight by gender. Education and wealth are proxied by neighbourhood (Jiedao, the finest Census unit in China) average education years and housing wealth (housing wealth takes up 71.35% of household wealth in China (Li & Fan, 2020)). Surprisingly, we find no significant differences in the response elasticity across gender and weight. People older than the median age (about 30) are more sensitive to air pollution by reducing activities more. Yet further decomposition by age groups suggest a U shape response: people of 30-40 years old have higher response elasticity and the continuously decreasing towards younger and older age groups (Supplementary Figure 6), which is not consistent with the physical health risk of pollution exposure.

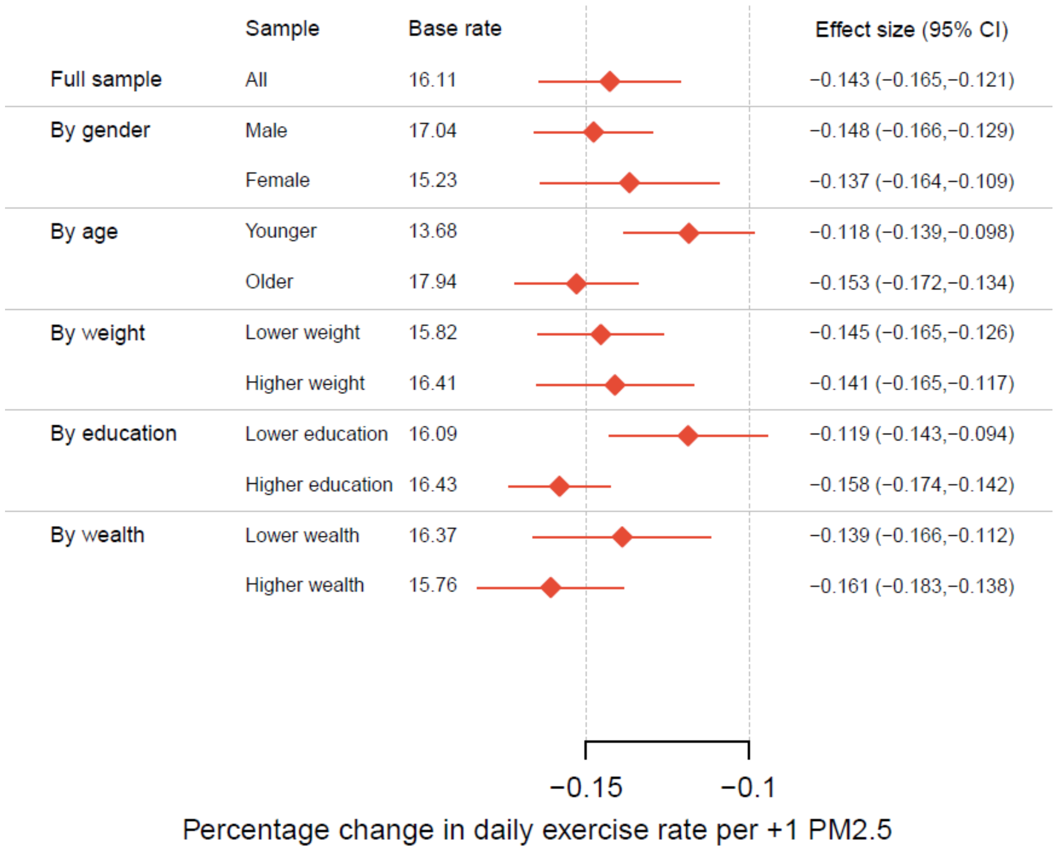


Figure 6. Effect of PM2.5 on daily outdoor exercise rate for different subgroups. The dots are point estimates, and the lines are 95% confidence intervals. Percentage changes are obtained by dividing the base rate for each subgroup. We use median splits for all dimensions except for gender. For weight, we conduct median splits for each gender separately. Education is measured by the neighbourhood average education year (i.e., Jiedao, the finest Census unit in China). Wealth is proxied by the neighbourhood average housing wealth per capita. All the coefficients are highly significant after multiple hypothesis testings. The coefficients across age and education groups are significantly different when under t-tests.

People within wealthier neighbourhoods do reduce outdoor exercise more when the ambient pollution level is high (especially for the highest wealth quartile, see Supplementary Figure 7), yet education is a stronger predictor of response heterogeneity than wealth. The marginal effects of PM2.5 increase with neighbourhood education: As shown in Figure 7a, a 10 μg/m^3 increase in ambient PM2.5 concentration reduces the proportion of people doing outdoor exercise in the lowest education neighbourhood (average education below 9 years; middle school and below) by

1.08% (95% CI: 0.71-1.44%), which continuously increase with education level till 1.71% (95% CI: 1.50-1.92%) for the neighbourhoods with average education above 12 years (college and above). The results from binned regressions suggest significantly larger outdoor exercise reduction in more educated neighbourhoods at all pollution categories (Figure 7b). The most educated neighbourhoods have 27.8% and 49.2% reduction in outdoor exercise when the ambient air pollution is heavy and severe; while the least educated neighbourhoods only have 11.3% and 18.0% reduction.

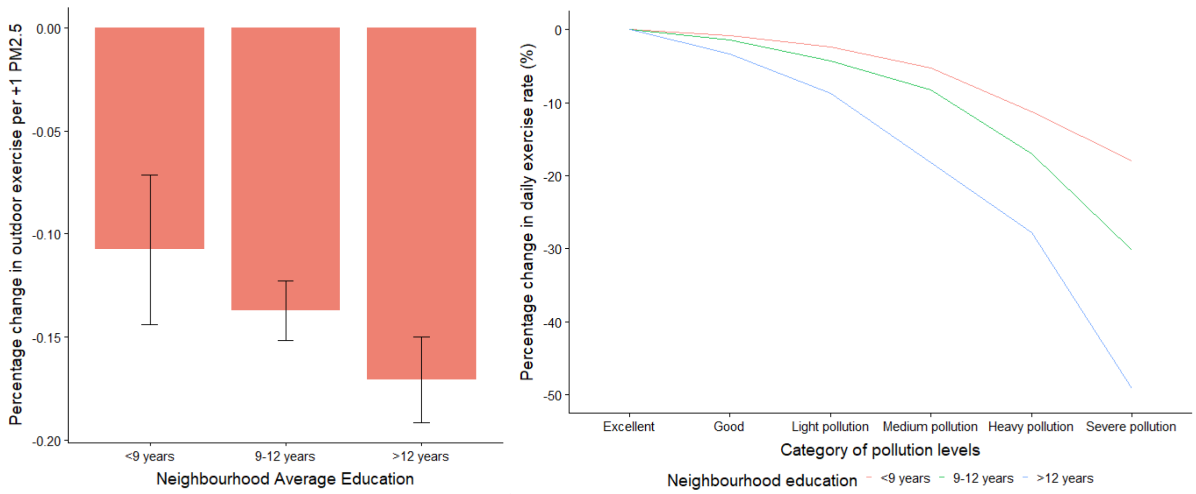


Figure 7. Change in outdoor exercise rate by neighbourhood education. **a,** Marginal response to PM2.5 by neighbourhood education. **b,** Categorical responses to air pollution levels by neighbourhood education. Education is measured by average education years within each neighbourhood (Jiedao) and is obtained from the 2010 Census of China. "<9 years", "9-12 years" and "> 12 years" correspond to "middle school and below", "high school" and "college and above" respectively.

Potential mechanisms for disparities

As reducing outdoor exercise has no monetary cost, the disparity in such avoidance behavior is likely to be driven by information. Previous studies suggest two non-market factors playing essential roles in avoidance behaviors: access to accurate pollution information (objective) and awareness of pollution health impacts (subjective) (Greenstone et al., 2021). In principle, all people in our sample should have adequate access to objective pollution information as they are all smartphone users with good internet access. Yet, in reality, people might ignore pollution information on a day-to-day basis.

To test whether access to objective information itself is a key driver for inequality, we take advantage of the pollution alert system of China. Specifically, the Municipal Government's Emergency Office of cities in China will issue an official alert when the daily average AQI is expected to be above the heavy pollution threshold (i.e., 200). The alerts are of different levels: Blue and yellow alerts indicate short-term (about 1-2 days) heavy pollution and can be issued in real-time. In contrast, orange and red alerts indicate that a heavy to severe pollution sequence is predicted to last. Such higher level alerts will need to be issued 24 hours in advance, and are under the regulation of provincial and national governments. City governments circulate the alerts through broadcast, TV, internet, newspaper, and Weibo (microblog platform in China, which is similar to Twitter). When the pollution alerts reach orange and red levels, text messages are sent to citizens to encourage the adoption of avoidance behavior[3]. If lower education people are not taking action solely because of a lack of access to pollution information, the pollution alerts should serve as an effective way to increase their avoidance behaviors by increasing the saliency of pollution information.

To compile a comprehensive pollution alert database, we collect the official Weibo accounts of all city governments in China and scrape all their historical posts in 2017. Using text analysis techniques, we extract the detailed pollution alert history of 76 cities. As displayed in Supplementary Figure 8, the probability of having pollution alerts issued increases with daily average AQI level. Only less than one fourth of the heavy pollution sequences are successfully predicted, providing variations to compare whether pollution alerts increase avoidance behaviors.

In contrast to the behavioral pattern predicted by the access to objective information channel, we find that people in lower educated neighbourhoods are also much less responsive to pollution alerts (Table 4). On days without pollution alerts, people within the highly educated neighbourhood reduce exercise rate two times the magnitude of the lowest education neighbourhood (18.27% and 9.93% respectively). With alerts issued, the gap is enlarged rather than narrowed. Low (blue or yellow) and high (orange or red) levels of pollution alerts reduce exercise rate of people within the high education neighbourhoods (>12 years) by an additional 6.99% and 13.25%, while the impacts of alerts are statistically insignificant for people in the low education neighbourhoods (<9 years). As longer pollution sequences are more likely to have pollution alerts issued, we also test the effect of pollution alert on the first heavy polluted days and the results also show consistent elasticity gradient by education (Supplementary Table 4). This suggests that solely bringing citizens' attention to air pollution information through pollution alerts cannot close the avoidance behavior gap, hinting at the existence of subjective differences in perceived pollution severity and health impacts.

[3] When alerts are issued, heavy measures are also implemented to regulate industrial, construction and other types of pollution activities.

Table 4. The effect of pollution alerts on outdoor exercise rate by education.

	Outdoor exercise rate (percentage change)			
	All	< 9 years	9-12 years	>12 years
	(1)	(2)	(3)	(4)
Heavy Pollution × Red/Orange Alert	-11.6007***	-6.5250	-12.0874***	-13.2476***
	(2.2231)	(5.2838)	(3.3818)	(1.9435)
Heavy Pollution× Blue/Yellow Alert	-5.8709*	1.0289	-3.8192*	-6.9856***
	(2.0323)	(3.7488)	(1.9017)	(1.7080)
Heavy Pollution	-10.9118***	-9.9344***	-12.0780***	-18.2737***
	(1.6183)	(1.7368)	(1.5257)	(2.5024)
dependent variable mean	16.96	17.11	17.76	16.78
weather controls	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
day-of-week FE	Yes	Yes	Yes	Yes
city-by-month FE	Yes	Yes	Yes	Yes
Observations	12,031,198	1,313,414	3,512,575	1,399,661
Adjusted R^2	0.1235	0.1251	0.1307	0.1250
Note:	*p<0.1; **p<0.005; ***p<0.001			

To have a direct understanding of the subjective information held by citizens, we conducted a large-scale survey with colleagues at MIT Sustainable Urbanization Lab in Zhengzhou, a central city of China with winter monthly PM2.5 above 100 μg/m^3 (see Supplementary Note 1 for detailed information)[4]. In the survey, we asked the respondents questions about their subjective perception of local air pollution. As shown in Table 5, even though all our respondents are from the same city and work in the same CBD area, the perception of local air pollution severity continuously increases with education level. Highly educated people are also more aware of the severe impacts local air pollution impose on their health. These results suggest that different subjective perceptions about air pollution and its corresponding health consequences are likely to be the key mechanism underlying the differential outdoor exercise reduction in response to the same air pollution information across people with different socio-economic status.

[4] The survey was conducted in July 2019. All our survey participants work at the CBD area of Zhengzhou and have access to the same objective pollution index in their daily life.

Table 5. Subjective perception of local air pollution and health impacts.

		Local air pollution severity (1: very good; 5: Terrible)		Local air pollution health impacts (1: no impact; 5: Severe impact)	
		Mean	SD	Mean	SD
(1)	Middle school and below (<9 years)	3.57	[1.16]	3.49	[1.15]
(2)	High school (9-12 years)	3.89	[1.02]	3.86	[1.00]
(3)	College and above (>12 years)	4.36	[0.81]	4.09	[0.88]
t-test (1)-(2) p-value		0.03**		0.01**	
t-test (1)-(3) p-value		0.00***		0.00***	
t-test (2)-(3) p-value		0.00***		0.00***	

Notes: *p<0.1; **p<0.05; ***p<0.01. Results from large-scale survey conducted in Zhengzhou, a city in China with monthly PM2.5 level above 100 $\mu g/m^3$ in winter. The pollution perception questions are elicited using the 5-level likert-scale.

An alternative hypothesis to the awareness-driven inequality is adaptation capacity. For example, people of lower education have higher likelihood to actively commute due to lower car ownership. As commuting trips are less flexible, the differences in pollution response elasticity by education might reflect different compositions in leisure and commuting exercises. We thus decompose outdoor exercise into exercise taking place during commuting (ending at 7:30-9:30 AM or 17:30-19:30 PM) and non-commuting times of workdays. As shown in Supplementary Figure 9, exercise during the commuting time is less responsive to air pollution, especially for people in the low-education neighbourhoods. However, in both commuting and non-commuting times, substantial pollution avoidance disparity exists between neighbourhoods of different education levels. Adaptation constraints in the commuting setting is thus unlikely to be the full determinant of the avoidance behavior gap. Furthermore, we also find no evidence that people in high education neighbourhoods increase indoor exercise more than low education neighbourhoods (Supplementary Table 5), indicating that ability to substitute activity indoors (e.g., due to larger houses or more exercise equipment) is not the key driver to pollution avoidance differences as well.

Discussion

This paper documents robust causal effects of air pollution on urbanites' outdoor physical exercise: A 10 $\mu g/m^3$ increase in ambient PM2.5 concentration reduces the proportion of people doing outdoor exercise by 1.43%. We find discontinuous reduction around the government-set heavy pollution threshold, suggesting that the pollution information program plays an important role in guiding avoidance behaviors. Although pollution information is effective, there exists striking inequality in avoidance behaviors across neighbourhoods. The most educated neighbourhoods are nearly four times more sensitive to heavy air pollution by reducing outdoor exercise more than the least educated neighbourhoods.

There are several limitations for this study. The most important drawback is the unrepresentative sample coverage. As people using the smartphone app to exercise are younger, older people are underrepresented in this dataset. In addition, both income and education are measured at neighbourhood, rather than individual level. Measurement errors will inevitably exist when using the coarser measurements (which will bias the results towards 0). Lastly, an ideal setting to test the impacts of air pollution information is to compare behaviors before and after 2013, when the pollution information program was established in China. As we do not have exercise data before 2013, we can only measure the combined effect of visibility and air pollution index. Though useful for estimating the health implications of avoidance behaviors, the results are not well-suited for quantifying the benefits of government issued pollution information.

The results of this study have three important policy implications. First, as pollution information programs worldwide aim to nudge people to reduce outdoor activity, our findings suggest that solely relying on pollution information to facilitate pollution avoidance could enlarge the exposure inequality across socio-economic groups. Policymakers should be recognizant of the distributional consequences when weighing between public mitigation and private avoidance efforts.

Second, our results suggest that the gaps across education are primarily driven by differences in subjective perceptions of pollution severity and health impacts. The awareness gaps cannot be bridged by providing accurate pollution information and issuing alerts. Governments should pay more attention to delivering tailored education on the health consequences of heavy air pollution if they choose to use information policy as an instrument. With the increasing attention to smart city initiatives, city governments are paying increasing attention to the supply of micro-level information. How democratization of information can really democratize knowledge and thus stimulate beneficial behavioral changes require more research efforts.

Finally, as significant behavioral disparities exist in zero-cost avoidance behavior like physical exercise, imperfect information is likely to be pervasive in the pollution market due to asymmetric awareness. In principle, optimal environmental regulations should equate the marginal abatement cost with the marginal social benefit of pollution reduction. The existing literature using revealed preferences to quantify people's marginal willingness-to-pay (MWTP) for air quality improvement usually rely on market behaviors and have the explicit assumption of perfect information. The findings from this paper suggest that relying on revealed market behaviors to estimate marginal willingness to pay (MWTP) for air quality improvement would underestimate how people with lower socio-economic status value air quality. Such information asymmetry still exists even when governments supply pollution information. As cities worldwide increasingly adopt smart sensing technologies to provide more accurate micro-level pollution information, more attention should be paid to how people respond to information.

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Appendix

A. Supplementary Notes

Supplementary Note 1. Information about the Zhengzhou survey.
The survey took place in Zhengzhou, a city of 10 million inhabitants that is the capital of Henan province, China. The seasonal variation of air pollution is high, with winter heating leading to a monthly average PM2.5 level above 100 μg/m^3. Our survey was conducted in July, 2019. Our sampling frame is non-automobile commuters, whose job location is around Zhengzhou's new Central Business District (CBD) area. The team visited 95 local companies covering 18 sectors around the CBD area. The surveys are administered online on Qualtrics platform while surveyors are alongside respondents to answer any questions about the questions.

For more information about the survey, please refer to:
Fan, Y., Palacios, J., Arcaya, M., Luo, R., & Zheng, S. (2021). Health perception and commuting choice: a survey experiment measuring behavioral trade-offs between physical activity benefits and pollution exposure risks. *Environmental Research Letters*. https://doi.org/10.1088/1748-9326/abecfd

B. Supplementary Figures

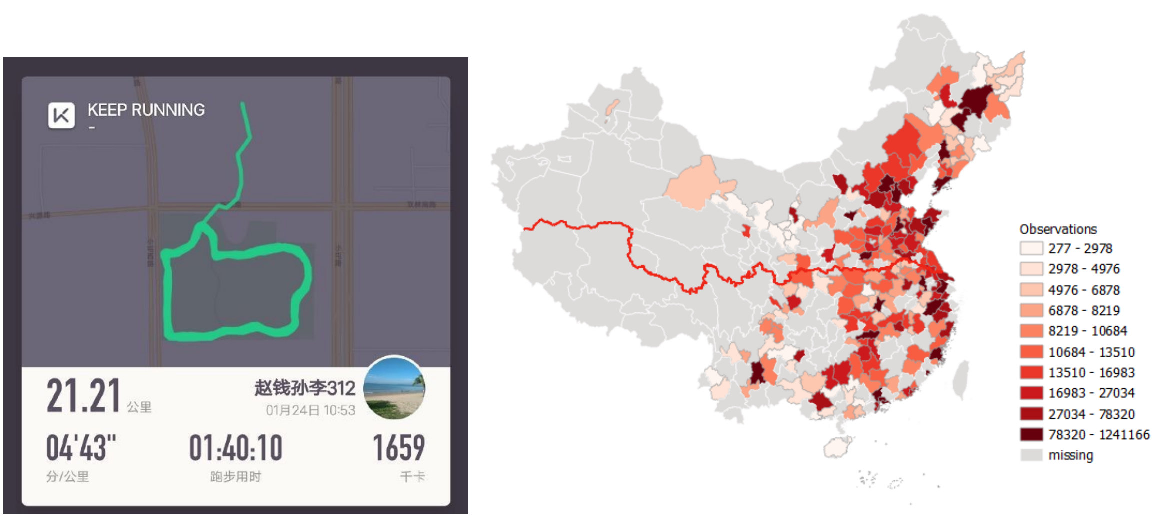

Figure S1. Geotagged exercise record and its spatial distribution.

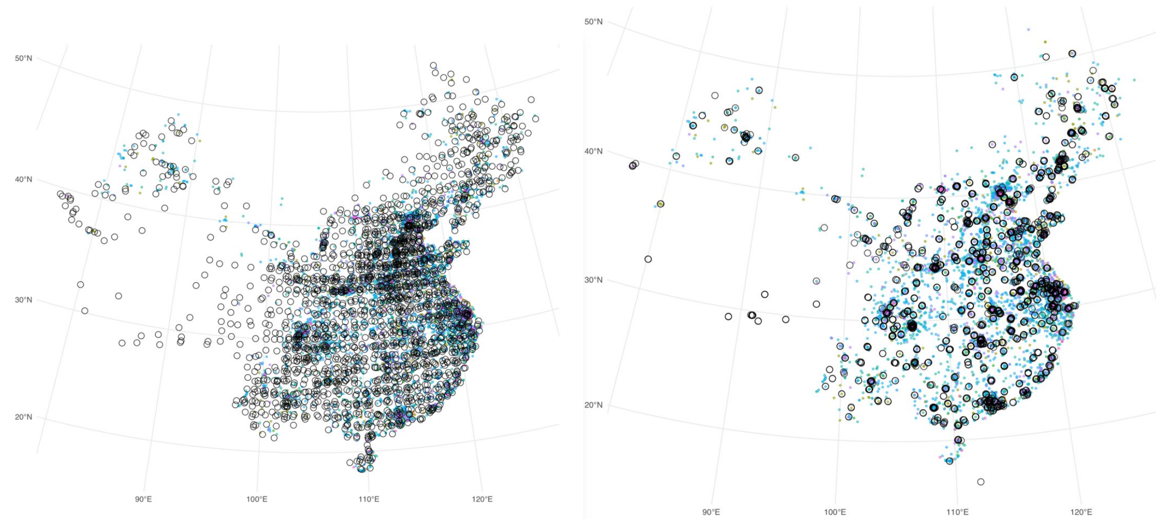

Figure S2. Meteorological (left) and air pollution (right) monitoring stations all over China.

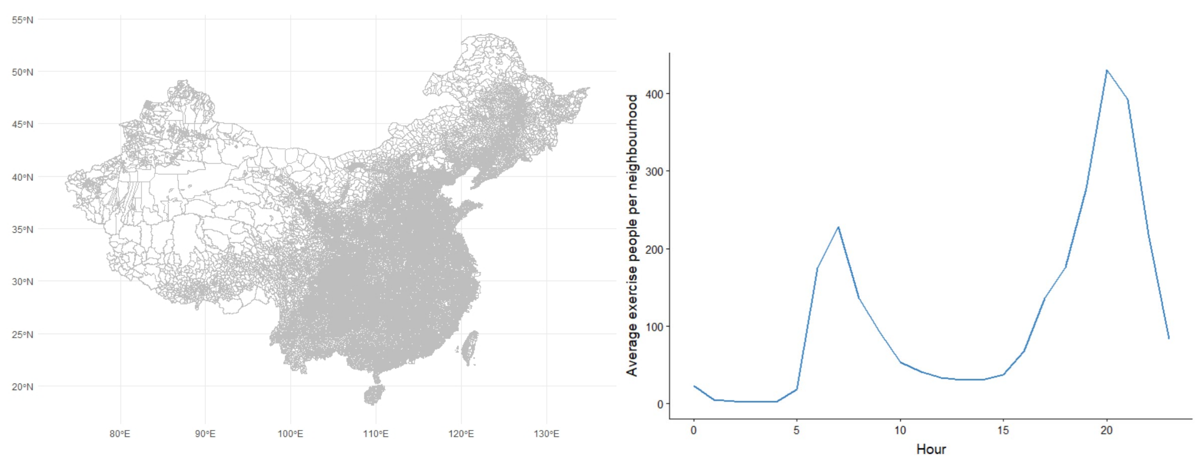

Figure S3. (a) Spatial granularity of neighbourhood (Jiedao); (b) Average number of people doing outdoor exercise in each neighbourhood per hour.

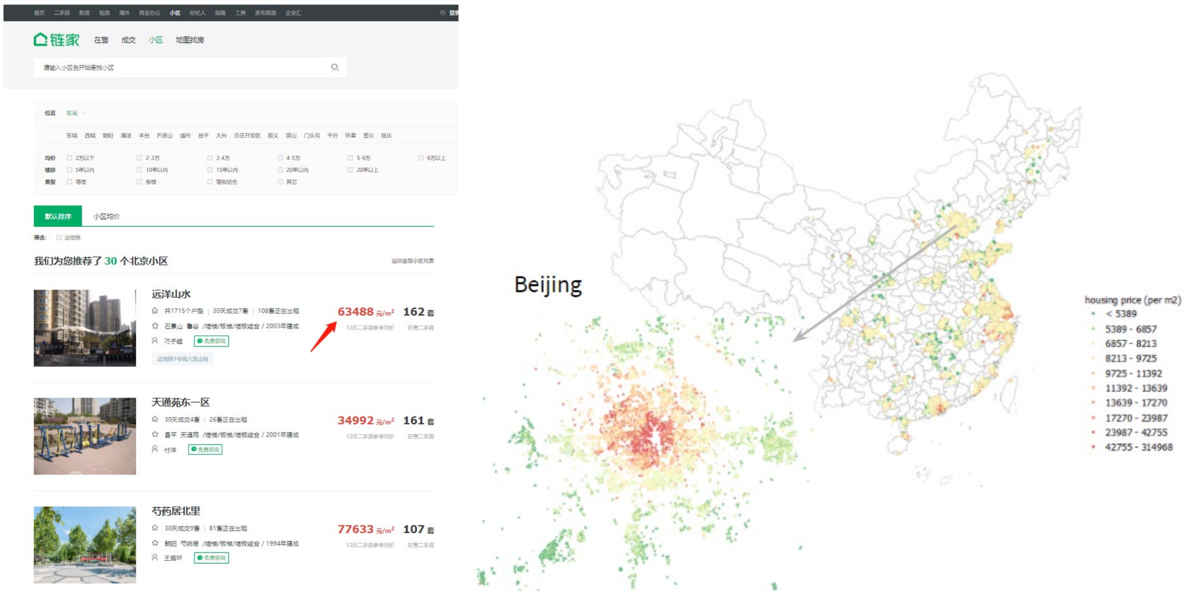

Figure S4. Housing price data from Lianjia (https://m.lianjia.com/) and the price heatmap for each neighbourhood. Data of Beijing is zoomed in (rescaled the price) to display the spatial granularity of the data.

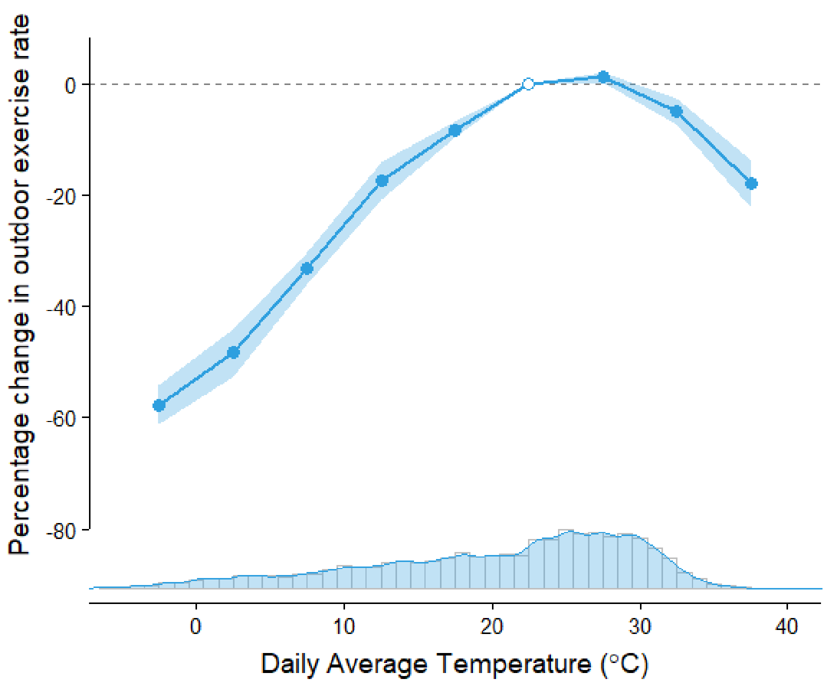

Figure S5. Daily average temperature and percentage change in outdoor exercise rate. Points show the regression coefficient for each temperature bin (with 20-25 °C as baseline), and the shaded areas display the 95% confidence interval. Histogram displays the distribution of temperature.

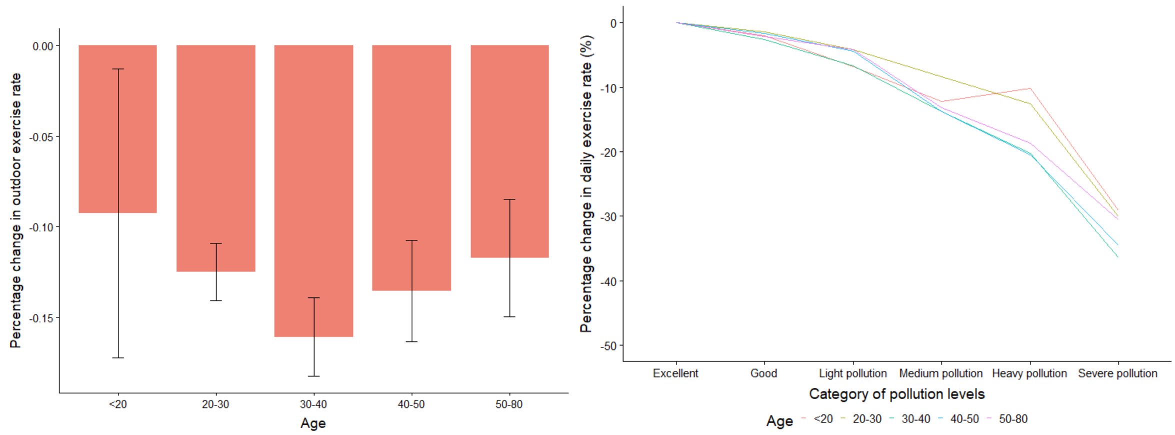

Figure S6. Marginal effect of PM2.5 on outdoor exercise rate by age group.

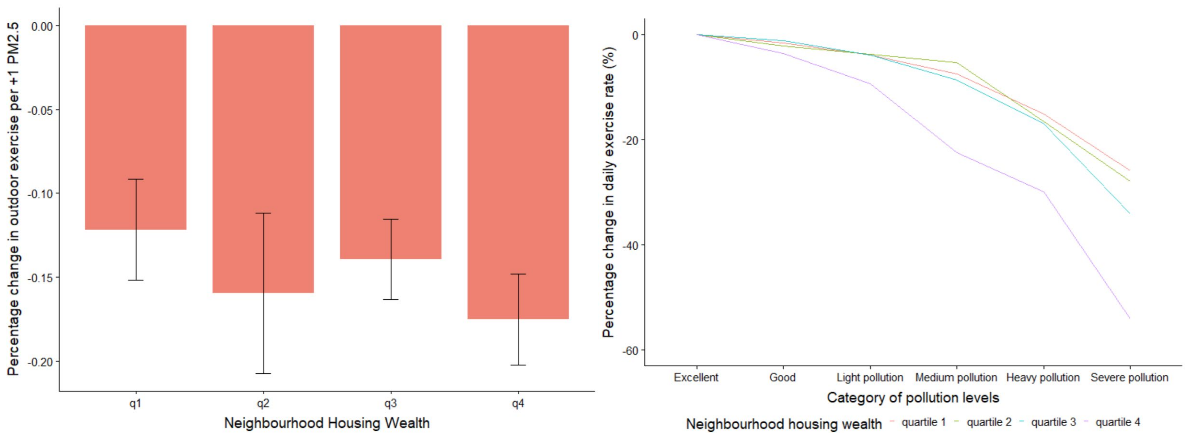

Figure S7. Change in outdoor exercise rate by neighbourhood housing price. **a,** Marginal response to PM2.5 by income quartiles. **b,** categorical responses to air pollution levels by income quartiles.

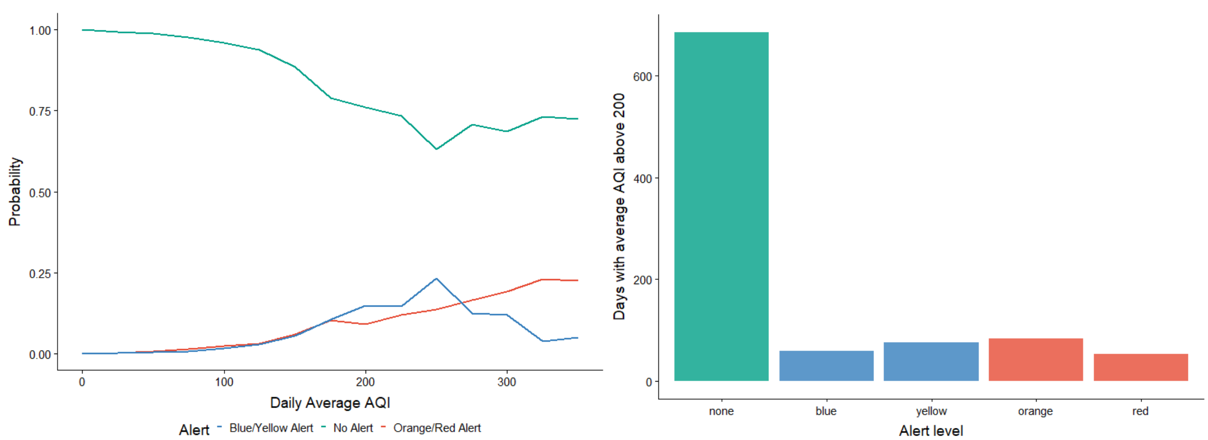

Figure S8. Pollution alerts in 76 cities. **a,** Daily average AQI level and alert probability. **b,** Heavy pollution days covered by different levels of alerts.

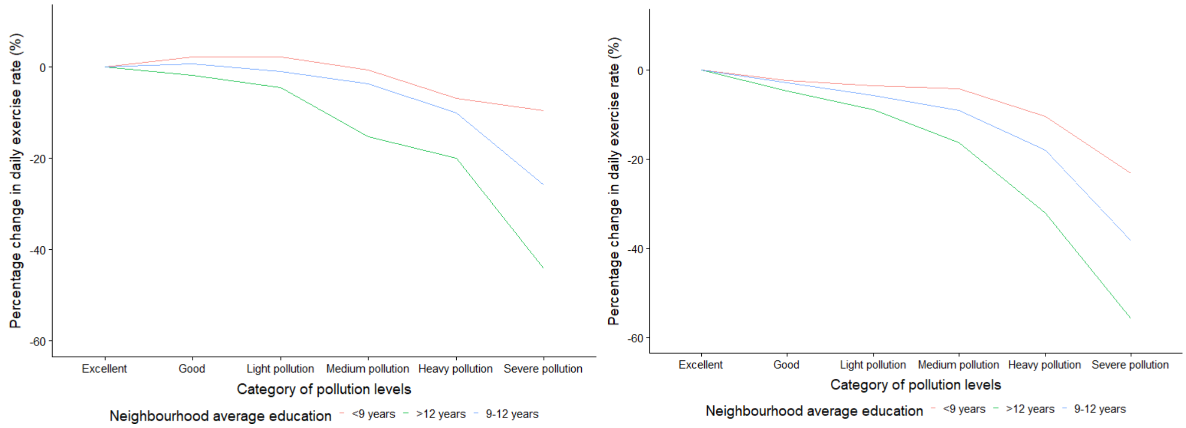

Figure S9. Pollution and outdoor exercise rate by education groups during commuting times (left) and non-commuting times (right).

C. Supplementary Tables

Table S1. Marginal effect of air pollution on outdoor exercise duration for people who exercised.

	Outdoor exercise duration (minute)			
	(OLS)	(2SLS)	(OLS)	(2SLS)
	(1)	(2)	(3)	(4)
AQI	-0.0049***			
	(0.0010)			
PM2.5			-0.0053***	
			(0.0012)	
AQI IV		-0.0060***		
		(0.0014)		
PM2.5 IV				-0.0056***
				(0.0015)
dependent variable mean	42.5178	42.5178	42.5178	42.5178
First stage F-stats		85.1221		69.0343
weather controls	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
day-of-week FE	Yes	Yes	Yes	Yes
city-by-month FE	Yes	Yes	Yes	Yes
Observations	3,624,912	3,210,991	3,624,883	3,210,175
Adjusted R^2	0.3451	0.3448	0.3451	0.3448
Note:	*p<0.01; **p<0.005; ***p<0.001			

Table S2. Marginal effect of air pollution on indoor exercise rate.

	Indoor exercise rate (percentage change)			
	(OLS)	(2SLS)	(OLS)	(2SLS)
	(1)	(2)	(3)	(4)
AQI	-0.0010			
	(0.0032)			
PM2.5			0.0015	
			(0.0035)	
AQI IV		-0.0045		
		(0.0049)		
PM2.5 IV				0.0012
				(0.0057)
dependent variable mean	16.12	16.12	16.12	16.12
First stage F-stats		37.1101		38.0701
weather controls	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
day-of-week FE	Yes	Yes	Yes	Yes
city-by-month FE	Yes	Yes	Yes	Yes
Observations	20,437,250	17,964,029	20,436,925	17,958,932
Adjusted R^2	0.2406	0.2411	0.2406	0.2411
Note:	*p<0.01; **p<0.005; ***p<0.001			

Table S3. Donut Regression Discontinuity results around AQI 200 by different settings.

	donut range			
kernel	0	5	10	15
epanechnikov	-4.727**	-9.235***	-9.84***	-8.360**
	(2.401)	(2.689)	(3.088)	(3.380)
uniform	-5.625**	-9.984***	-10.127***	-8.638**
2.835907	(2.836)	(2.909)	(3.219)	(3.658)
triangular	-4.431*	-8.585***	-9.834***	-9.015***
	(2.303)	(2.557)	(3.052)	(3.453)

Note: *p<0.1; **p<0.05; ***p<0.01

Table S4. Effects of pollution alerts on outdoor exercise by education for the first heavy pollution day.

	Outdoor exercise rate (percentage change)		
	(< 9 years)	(9-12 years)	(> 12 years)
	(1)	(2)	(3)
Heavy Pollution × Red/Orange Alert	-1.3641	-15.5823**	-18.0293***
	(8.1798)	(4.7071)	(3.8497)
Heavy Pollution × Blue/Yellow Alert	3.0751	-3.8800	-11.6966***
	(4.4087)	(2.7953)	(2.6426)
Heavy Pollution	-11.5439***	-10.0196***	-13.4550***
	(1.7675)	(1.9507)	(2.4281)
weather controls	Yes	Yes	Yes
individual FE	Yes	Yes	Yes
day-of-week FE	Yes	Yes	Yes
city-by-month FE	Yes	Yes	Yes
Observations	1,301,873	3,482,785	1,390,045
Adjusted R^2	0.1257	0.1309	0.1248
Note:	*p<0.01; **p<0.005; ***p<0.001		

Table S5. Marginal effect of air pollution on indoor exercise rate by education.

	Percentage change in indoor exercise		
	(<9 years)	(9-12 years)	(> 12 years)
	(1)	(2)	(3)
PM2.5	-0.0052	-0.0020	0.0008
	(0.0132)	(0.0070)	(0.0058)
dependent variable mean	21.23	21.38	21.5
weather controls	Yes	Yes	Yes
individual FE	Yes	Yes	Yes
day-of-week FE	Yes	Yes	Yes
city-by-month FE	Yes	Yes	Yes
Observations	2,442,311	5,993,478	1,794,395
Adjusted R^2	0.2427	0.2441	0.2470
Note:	*p<0.01; **p<0.005; ***p<0.001		