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Haze and crime: Evidence from court judgments in China

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ABSTRACT

Utilizing 1.5 million court judgment files in China during 2015–2018, we investigate the causal relationship between short-term air pollution exposure and crime rates. Using thermal inversion as the instrument for air pollution, we find that a 10 μg/m^3 increase in daily $PM_{2.5}$ leads to a 1.583% increase in the daily crime rate of intentional injury, whereas air pollution has no statistically significant effect on the crime rates of dangerous driving, theft, and robbery. Using detailed characteristics at the case and criminal level, we show that perpetrators in these pollution-induced crimes are more likely to be repeat offenders, non-accomplices, unarmed offenders, and cases involving voluntarily surrender are more affected. In addition, we find that the salience of pollution plays an important role in shaping criminals' moods to commit crimes. Our results have implications for measuring the social costs of pollution and designing crime reduction policies.

1. Introduction

Crime incurs significant social costs, and understanding the underlying causes of crime has important policy implications for the prevention of crime. A growing strand of literature has studied the impact of environmental factors, such as air pollution, rainfall, ambient light, and temperature on crime or aggressive behaviors (Baysan et al., 2019; Doleac & Sanders, 2015; Jacob et al., 2007; Ranson, 2014; Tealde, 2022). While these previous works show the importance of such environmental factors on incidences of crime, a comprehensive characterization of the profile of individuals prone to pollution-induced criminal behavior remains lacking. Understanding this aspect is important for tailoring crime-reduction policies and comprehending the mechanisms underlying weather-induced crimes. We follow this line of inquiry to explore how crime is affected by contemporaneous air pollution exposure by employing case level crime data in China. Importantly, we leverage on the detailed case and individual level data to zoom in to the factors affecting individual behaviors, especially the individuals that are the most prone to pollution-induced criminal behavior.

Unraveling the causal mechanisms underlying the relationship between short-term pollution exposure and aggression poses a challenge in observational studies. In general, previous research across the domains of biology, epidemiology, and psychology has documented two primary categories of pathways—physiological and psychological. Firstly, exposure to air pollution may elevate blood pressure, hormones, insulin resistance, and biomarkers of oxidative stress and inflammation, potentially leading to an increase in criminal or violent activities (Li et al., 2017; Rammal et al., 2008). Secondly, air pollution has been linked to heightened levels of stress, anxiety, impatience, and anti-social behavior (Chew et al., 2021; Lu et al., 2018, 2020; Power et al., 2015; Sass et al., 2017). We try to

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add to the discussion on the mechanisms, introducing a fresh perspective of the importance of pollution salience in affecting potential criminals' behaviors, which enriches our understanding of the mechanisms underlying pollution-induced crimes.

Based on 1.5 million court judgment files in China from 2015 to 2018, we examine how short-term air pollution exposure affects criminal behavior, focusing on dangerous driving, intentional injury, theft, and robbery. We construct daily crime rates for each city and match them to air pollution levels that day. To address the potential endogeneity of air pollution due to human activities, we exploit the phenomenon of thermal inversion as an instrumental variable for air pollution. Our empirical specifications incorporate a rich set of fixed effects, including city-year, city-month, year-month, day-of-month, day-of-week, and holiday fixed effects. In addition, we control for a variety of weather conditions that may affect criminal activities and correlate with pollution levels, including temperature, wind speed, precipitation, sunshine duration, and atmospheric pressure.

Our analyses present three main findings. First, we find that a 10 $\mu g/m^3$ rise in daily $PM_{2.5}$ (fine particulate matter) leads to a significant 1.583% increase in the daily crime rate of intentional injury, whereas air pollution has no statistically significant effect on the crime rate of dangerous driving, theft, and robbery. Additionally, we find that the effects of air pollution on crime are nonlinear, which means individuals have a disproportionally stronger response to pollution as the pollution level increases. The results are similar if we control for atmospheric conditions more flexibly, use the Air Quality Index (AQI) as an alternative measure of air pollution, utilize Poisson pseudo-likelihood regression (PPML),[1] incorporate different fixed effects, or employ an alternative instrument variable (the number of thermal inversion occurrences instead of thermal inversion strength). In addition, we find contemporaneous rather than lagged effects of pollution on crime, and we do not find evidence of intertemporal shifting.

Second, we exploit more detailed data to identify the individuals and contexts that are most prone to pollution-induced crimes. Specifically, we explore the heterogeneity of the results with respect to both the city and offenders' characteristics. At the city level, we find that the impact is more pronounced in cities with weaker governance capacity, lower education levels, and higher living pressure relative to their level of economic development. Regarding the individual characteristics, we find that criminal behavior among young and male offenders is more likely to be affected by pollution than among old and female offenders. Furthermore, by coding rich information from court judgment files, at criminal case level, we find pollution-induced intentional injuries have a higher probability of voluntary surrender than non-surrender cases, suggesting the offenders are more likely to regret crimes committed on polluted days. Additionally, it is worth highlighting that intentional injury cases involving repeat offenders, single offenders, or unarmed offenders are more affected by pollution compared to cases involving first-time offenders, accomplices, or armed offenders. Moreover, we find that crimes with relatively less severe consequences are more susceptible to air pollution impacts.

Lastly, we further examine the mechanism through which pollution may induce crime. We begin by estimating a horserace model that includes both $PM_{2.5}$ and ozone on the right-hand side of the regression equation. The empirical results reveal that only visible $PM_{2.5}$ significantly affects crime rates, whereas invisible ozone does not exhibit a comparable effect. This finding is robust to instrumenting ozone with upwind ozone from nearby cities, to flexible controls for weather conditions, and to the use of the PPML estimator. Given that both $PM_{2.5}$ and ozone are acknowledged in the literature for their capacity to induce changes in brain chemistry and physiology in a comparable manner, their differential effects on crime point to a role for pollution salience (further discussed in Section 5.3). Moreover, $PM_{2.5}$ had no significant impact on crime before the widespread dissemination of the influential environmental documentary "Under the Dome" in 2015, which provides rich information about pollution and raises public awareness about pollution issues in China (Tu et al., 2020). In addition, the pollution effect on crime is significantly stronger on days when the visibility is *unexpectedly* low relative to what would be predicted by local seasonal patterns and weather conditions, periods we interpret as days when air pollution is more visually salient to residents. While *actual* pollution can alter people's behavior through both physiological and psychological changes, *perceived* pollution can only affect individuals' behavior psychologically. In line with this distinction, experimental evidence shows that merely observing high pollution levels—even in the absence of direct exposure—can induce negative moods, and make individuals more impatient and anti-social (Chew et al., 2021). We would like to propose pollution salience as a complementary mechanism that helps interpret the observed pollution effect on crime rates. Taken together, these results suggest that pollution salience plays a complementary role in shaping pollution-induced crime.

Our work contributes to the current literature in the following aspects. Among the existing body of literature on the causal effect of pollution on crime, three papers are particularly relevant to our study. Herrnstadt et al. (2021) and Bondy et al. (2020) employed aggregated administrative crime data to investigate the impact of air pollution on crime in the cities of Chicago and London, respectively. Additionally, by utilizing national incidence-level crime data in the United States and aggregating them at the county-date level, Burkhardt et al. (2019) provided a much broader geographic coverage for studying the relationship between short-term air pollution and crime. In contrast, our disaggregated data on a national scale, encompassing detailed information on each offender, allow us not only to leverage regional variation, but also help us delineate the profile of pollution-induced criminals. Therefore, by utilizing this rich information on criminal cases and offenders, we undertake a more comprehensive examination on individuals who are more vulnerable to engage in criminal activities, thereby complementing the existing literature. We find that individuals who are more likely to commit a crime due to air pollution are typically repeat offenders who experience lower mental and physical costs associated with committing crimes. Furthermore, they tend to act alone, without accomplices or the aid of weapons. Additionally, they are more likely to experience remorse and may voluntarily turn themselves in to law enforcement authorities. A quantile-style analysis suggests that the effect of air pollution on crime is mostly on the extensive margin rather than the intensive margin—it increases the number of crimes with less severe consequences, but does not increase the severity of the crimes. Our findings

[1] We implement the PPML with the algorithm developed by Correia et al. (2020). This algorithm allows us to incorporate high-dimensional fixed effects into the econometric model, adjust for over-dispersion, and obtain high rates of convergence efficiency.

underscore the necessity for targeted policy interventions, including rehabilitation and mental health support, to mitigate criminal tendencies among this vulnerable demographic. Additionally, community engagement and educational campaigns are crucial to raise awareness of the air pollution-crime relationship, while encouraging collaborative efforts and promoting responsible reporting, thereby fostering a safer and more secure society.

Second, we contribute to the literature by providing a fresh perspective on the potential mechanisms of air pollution-induced crimes. Short-term pollution exposure is associated with changes in hormone levels, oxidative stress, and inflammation; in turn, these chemical and physiological changes are linked to mood change and aggressive behavior (Li et al., 2017). Previous economic papers that examine the relationship between short-term pollution exposure and crime focus on the effects of the aforementioned pollution-induced physiological changes on mood or aggression. For example, Herrnstadt et al. (2021) discuss the potential mechanisms based on previous research in medicine, biology, and psychology that document the connections between pollution exposure and physiological changes that may trigger aggressive behavior; Burkhardt et al. (2019) refer to epidemiological and public health research and provide suggestive findings that pollution is an irritant that may trigger impulsive aggressive behavior; and Bondy et al. (2020) provide discussion on the potential channels based on the rational choice model of crime proposed by Becker (1968) and Ehrlich (1973), and conclude that the altered time preference used to discount criminals' perceived costs of punishment may be the most likely mechanism. Our results are consistent with these mechanisms, but they also point to a complementary channel centered on mood and salience. A growing body of evidence shows that pollution is associated with negative moods, including increased expression of negative emotions on social media (Du, 2023; Zarate Barrera, 2021). Building on this insight, we propose that the salience of pollution—its visibility and the attention it draws—can amplify negative mood responses that in turn impact criminal tendencies. This interpretation is supported by three empirical findings: (i) $PM_{2.5}$ has robust effects on crime whereas ozone does not; (ii) we find no detectable pollution effect on crime before air pollution became a salient public concern; and (iii) the estimated effects are larger on days when visibility is unusually low relative to local weather and seasonal conditions. While these results are not designed to deliver causal identification of the mechanism itself, they provide a new lens through which to interpret pollution-induced crime. Our finding does not imply dissent with prior literature; inhalation of air pollution undoubtedly directly triggers certain biochemical responses in human body. However, it is important to acknowledge the emotional changes brought by the salience of pollution.

Third, we are among the first to provide evidence on pollution-induced crime in China. As one of the largest developing countries with the most populous and rapidly advancing economies, China possesses socio-cultural and environmental dynamics different from those of western nations. Studies that document the relationship between air pollution and criminal activities have largely focused on cities in developed countries, such as Chicago and London, as well as the United States more generally (Jones, 2022; Herrnstadt et al., 2021; Burkhardt et al., 2019; Bondy et al., 2020; Chen & Li, 2020). Nevertheless, pollution levels in developing countries tend to be higher and legal systems weaker. Understanding how air pollution affects criminal activities in the developing world is crucial, not only to complement the literature on the social cost of air pollution but also to inform the development of effective air pollution control policies. In recent years, a handful studies explore the effect of air pollution on crime in developing countries, examining locales such as Mexico City, Almaty in Kazakhstan, and the state of Bihar in India (Batkeyev & DeRemer, 2023; Sarmiento, 2023; Singh & Visaria, 2021; Zarate Barrera, 2021). Compared to studies focusing on a single city or a region in developing countries, our research examines pollution-induced crimes on a national scale in China, covering wide demographic and geographic areas. In addition, in contrast to most atmospheric conditions that are difficult to change artificially in a short period, such as temperature and sunshine, air pollution can be effectively improved through reasonable regulations. By establishing the link between air pollution and crime, we can comprehensively evaluate the benefits and implications of air pollution control policies in reducing crime.

This paper proceeds as follows. Section 2 describes the data used and Section 3 introduces the identification strategy. Sections 4 and 5 present the main findings and discuss the mechanism. Section 6 concludes.

2. Data

We merge data on crime, pollution, weather, and thermal inversion to produce a dataset that spans a sample of 336 cities in China from 2015 to 2018.

Crime Data. Our crime data come from China Judgment Online (CJO), an official database of rulings that is overseen by the Supreme People's Court. The CJO data are widely used to measure crime rates in China in both the economics and legal literature (Ma et al., 2025; Ma et al., 2026; Lin and Xu, 2024). Ma et al. (2025) also conducted a detailed comparison between CJO data and official statistics from the *China Law Yearbooks* (CLY), providing external validation for the use of court judgment data to study criminal activities in China.

In 2013, as part of its efforts to increase judicial transparency and provide (non-binding) precedents for judges, the Supreme People's Court established the CJO website and required local courts at all levels to publish both contemporary and historical verdicts on this website. While there is a backlog in digitizing and disclosing historical verdicts, local courts are obligated to disclose all contemporary judgment files within seven days of trial completion, with exemptions granted for special cases such as those involving state secrets, juvenile criminal cases, disputes concluded through mediation, and divorce and adoption cases. For cases that the local courts decide not to release, the regulation requires disclosure of the case ID, name of the court, filing date, and an explanation. This set of rules has further institutionalized the publication of court decisions.

We collected court verdicts in China between 2015 and 2018 from the CJO. This includes 75 million judgment files, from which we identified more than 5 million criminal cases. To avoid double counting, we restrict the sample to first-instance criminal cases only. We further exclude cases in which the defendant was acquitted, although in practice, Chinese courts convict 99.4% of all criminal defendants. In addition, we limit the sample period to cases concluded before 2018 because cases from later on may not have been concluded or may not have been uploaded at the time of data collection.

Our analysis focuses on four types of crime: dangerous driving, theft, robbery, and intentional injury, which in total yield about 1.5 million cases for analysis. The focus on these four crime types is motivated by both data and research-design considerations. On the data side, restricting to these crimes helps mitigate concerns related to selective disclosure in court judgment data. As discussed before, although courts are statutorily required to disclose criminal judgments within seven days of trial completion, several categories of cases are exempt from disclosure. In practice, sexual crimes and certain family-related crimes are systematically excluded from publicly available court records and are therefore not comprehensively observable in the national judgment database. On the research-design side, our empirical strategy relies on daily variation in air pollution to identify short-term behavioral responses. Many economic crimes are poorly suited to this setting, as they are typically premeditated, unfold over longer horizons, and often lack a clearly defined offense date due to their continuous or repeated nature. Despite focusing on only four crime types, our sample captures a substantial share of overall criminal activity.[2]

Detailed legal definitions of the four crime types, as stipulated in the *Criminal Law of the People's Republic of China*, are provided in Table A.1. Conceptually, intentional injury captures violent behavior; theft and robbery represent property crimes, with robbery also involving a violent component; and dangerous driving reflects risk-taking behavior that endangers public safety. If mapping these four crime types to broader crime classifications in Law Yearbooks, dangerous driving falls under *crimes endangering public safety*, theft and robbery are classified as *property crimes*, and intentional injury belongs to *crimes infringing upon citizens' personal and democratic rights*.

We use a range of natural language processing methods to retrieve key information, including information on the legal and factual issues and parties involved in the cases. For each judgment file, we extract the following information: court in charge, trial and ruling dates, name of the judge and other court clerks, name and personal characteristics of the defendant, basic facts about the case, summary of trial process, and judicial reasoning provided by the judge. As for the case characteristics, we extract the date when the crime was conducted, whether the defendant reported himself/herself, and whether the case involves multiple defendants. At the defendant level, we extract the defendants' gender, age, employment status, and criminal history.

We are aware that there are several caveats concerning the data, but we argue that they do not affect the validity of our analysis. First, the conviction rate is admittedly not equal to delinquency, crime, or arrest rates. Given the high conviction rate of criminal defendants by the Chinese courts, however, it is safe to say that judicial data are a good reflection of the distribution of the arrest rate in China. Second, we cross-validate our data with the national-level official statistics in the Law Yearbooks of China from 2015 to 2018, published by the National Bureau of Statistics. For example, according to the Law Yearbooks of China (2018), there were approximately 300,000 property crime cases nationwide in 2017, of which about 200,000 involve theft (Chen, Liu, & Tang, 2022). Our data contains over 170,000 cases of theft crime, which account for more than 85% of the cases concluded in the year.

Second, it is worth noting that the publication of judicial opinions is incomplete and there are some missing files (Liu et al., 2022). This could occur for three reasons: (1) special cases such as those including cases involving state secrets, juvenile criminal cases, disputes concluded through mediation, and divorce and adoption cases are exempted from the disclosure requirement; (2) in the early years of the CJO, local courts may not have published all cases on the website (Ahl et al., 2019; Liebman et al., 2020); and (3) in 2021, it was reported that the CJO deleted a batch of 'politically sensitive' criminal cases from the website. However, neither of these issues is likely to substantially affect our analysis, for several reasons. First and foremost, as Chen, Liu, and Tang (2022) estimated, most provinces in China publish more than 80% of their criminal cases, with seven publishing more than 90%. Moreover, the disclosure rate does not vary a lot within the province across time, especially not across days, which is our unit of analysis. Also, a substantial share of these missing files belongs to those exempted cases, which is not the focus of our paper. We focus on criminal cases of theft, robbery, and intentional injury, which are not affected by the censoring rules. As for juvenile crime, according to official statistics, this accounts for only about 3% of total crimes in China. Second, the bulk of the missing cases documented in the literature were simply backlogs due to local courts' capacity constraints in the early years, and these files were added to the CJO later on. Third, we have been scraping the CJO website daily since 2018 for any updates, so any cases that were deleted after posting—including the batch deleted in 2021—would have been captured by our data. It is thus safe to believe that the incompleteness of judicial decision publication will not bias our findings. Most importantly, as we study short-term responses using daily variations, as long as disclosure rates do not systematically co-move with daily pollution shocks within a city across days, incomplete disclosure does not threaten our causal identification.

Air Pollution and Weather. Our air pollution data come from the China National Environmental Monitoring Center (CNEMC). The

[2] Over the 2015–2018 sample period, these four crimes account for 271 criminal cases per million population in our data, compared with 537 cases per million in the broader set of crimes examined by Ma, Pan, and Xu (2025). Thus, despite focusing on a smaller number of offense categories, our analysis still covers more than half of the total cases in their study. At the same time, their broader sample includes many offense types that are less well suited to the daily-frequency research design adopted in our paper, such as intellectual property infringements, financial crimes, and bribery.

data provide hourly readings of the Air Quality Index (AQI) and multiple pollutants including $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and ozone in more than 1600 stations throughout China. Since 2013, China has established and updated pollution monitoring stations at more than 1600 locations and posts real-time pollution levels on the website of China's Ministry of Ecology and Environment (MEE), as part of a nationwide real-time air quality monitoring and disclosure program. The program greatly expanded public access to pollution information, and significantly raised households' awareness about pollution issues (Barwick et al., 2019). PM is a major contributor to air pollution in China in the last decade or so, and the Chinese public has gradually become more aware of it since the disclosure of air pollution information. The AQI is a composite index of air quality, which is measured based on $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and ozone, with its value running from 0 to 500. In our study, we use $PM_{2.5}$ as the measure of air pollution in the main analyses and AQI for the robustness check. We calculate the daily mean $PM_{2.5}$ per city by averaging hourly readings from monitoring stations within a city.

The weather data are obtained from the China Meteorological Data Service Center (CMDSC), affiliated with the National Meteorological Information Center of China. The data provide daily weather conditions such as pressure, temperature, relative humidity, wind speed, wind direction, sunshine duration, and precipitation, from 745 basic and reference surface meteorological observation stations. Similar to our process with pollution data, we aggregate the daily value of each weather condition at the city-daily level by averaging the daily readings from all the stations within a city.[3]

Thermal Inversion. We collect thermal inversion data from the MERRA-2 product provided by the National Aeronautics and Space Administration (NASA). MERRA-2 is a global atmospheric reanalysis dataset with a resolution of 0.5° latitude × 0.625° longitude (c.a. 50 km × 60 km). It provides meteorological fields such as temperature at 42 pressure levels every six hours starting from 00:00 UTC. We define thermal inversion strength using the temperature differences between the two pressure levels closest to the ground, i.e., the difference between the above-ground and ground level temperatures.[4] In normal cases, the temperature at a higher altitude should be lower than the lower altitude, so a positive value indicates the existence of thermal inversion. The MERRA-2 satellite data provide the average temperature every 6 h; therefore, we calculate the average daily thermal inversion strength for each grid (0.5° latitude × 0.625° longitude) by averaging the four observations (at 2:00 a.m., 8:00 a.m., 2:00 p.m., and 8:00 p.m. Beijing time, respectively) on that day. For each city, we find all the grids within the city and then take the average as the daily thermal inversion strength in the city. We use the average value of daily thermal inversion strength per city in our main analyses and use the number of thermal inversion occurrences per city per day as an alternative definition of thermal inversion in the robustness check. Similarly, if the temperature difference between the second layer and the first layer near the ground is positive, it is marked as a thermal inversion. Since the MERRA-2 satellite data provide the average temperature every 6 h, we are able to calculate that the number of thermal inversion occurrences ranges from zero to four per 24 h.

2.1. Summary statistics

The combined dataset spans a sample of 336 cities in China from 2015 to 2018. The average population of a city in our sample is 4.26 million, with the largest city having a population of 33.9 million, and the smallest having a population of 0.1 million. In total, our sample covers approximately 1.39 billion people—more than 99% of China's population. In addition, our sample includes 569,410 dangerous driving cases, 629,874 theft cases, 276,121 intentional injury cases, and 37,972 robbery cases. Fig. 1 displays the geographical distribution of different types of crimes. As shown in Fig. 1, the distribution of crime exhibits substantial regional dispersion—the east and north have higher crime rates of dangerous driving and intentional injury, while the south has higher crime rates of theft and robbery. Fig. 2 presents the number of each crime type over our study period from 2015 to 2018. Overall, the total number of adjudicated cases rises over the sample period, although the patterns differ across crime categories. In particular, dangerous driving exhibits a steady upward trend and accounts for an increasing share of total cases, rising from approximately 35% to over 40%. Theft cases also increase over time but at a more moderate pace, representing roughly 40% of cases throughout the period. By contrast, intentional injury remains relatively stable, accounting for about 15–20% of total cases, while robbery constitutes a very small share, at less than 3%.

Table 1 presents the summary statistics for the variables at the city-daily level. For each type of crime, we calculate the daily crime rates for each city by dividing the daily number of each type of crime by the annual average population (in one million) of the city of the year. From 2015 to 2018, the average daily crime rate for each city is 0.304 per million people for dangerous driving, 0.305 for theft, 0.144 for intentional injury, and 0.019 for robbery. We then identify some case information from the document: whether the case involves voluntary surrender, first offense, accomplice, whether the perpetrators used weapons, whether the crime resulted in imprisonment, and if so, the length of the sentence. Panel B of Table 1 shows the case-level information. For all the four crimes in our sample, about 20% involve voluntary surrender, 12.4% involve first-time offense, 0.4% involve accomplices, and 7.2% involve the carrying of weapons. Regarding the sentences given, 79.4% of cases result in a sentence of less than one year, while 17.8% of cases result in a sentence of 1–5 years, and 2.8% of cases result in a sentence of five years or more. A single case may involve multiple perpetrators; for these we extracted all the perpetrators for each case. We identify the gender of roughly 79.6% of the offenders and the age for 56% of the offenders, with the remaining unidentified because no relevant information is mentioned in the judgment

[3] For a few cities that do not have monitoring stations, we use readings of the station nearest to the city centre as the daily mean for each weather condition.

[4] A lower altitude corresponds to a higher pressure level. The two layers closest to the ground are usually 1000 hPa and 975 hPa. Specifically, the 1000 hPa layer temperature corresponds to the surface conditions, and the 975 hPa layer measures conditions at approximately 350 m above sea level.

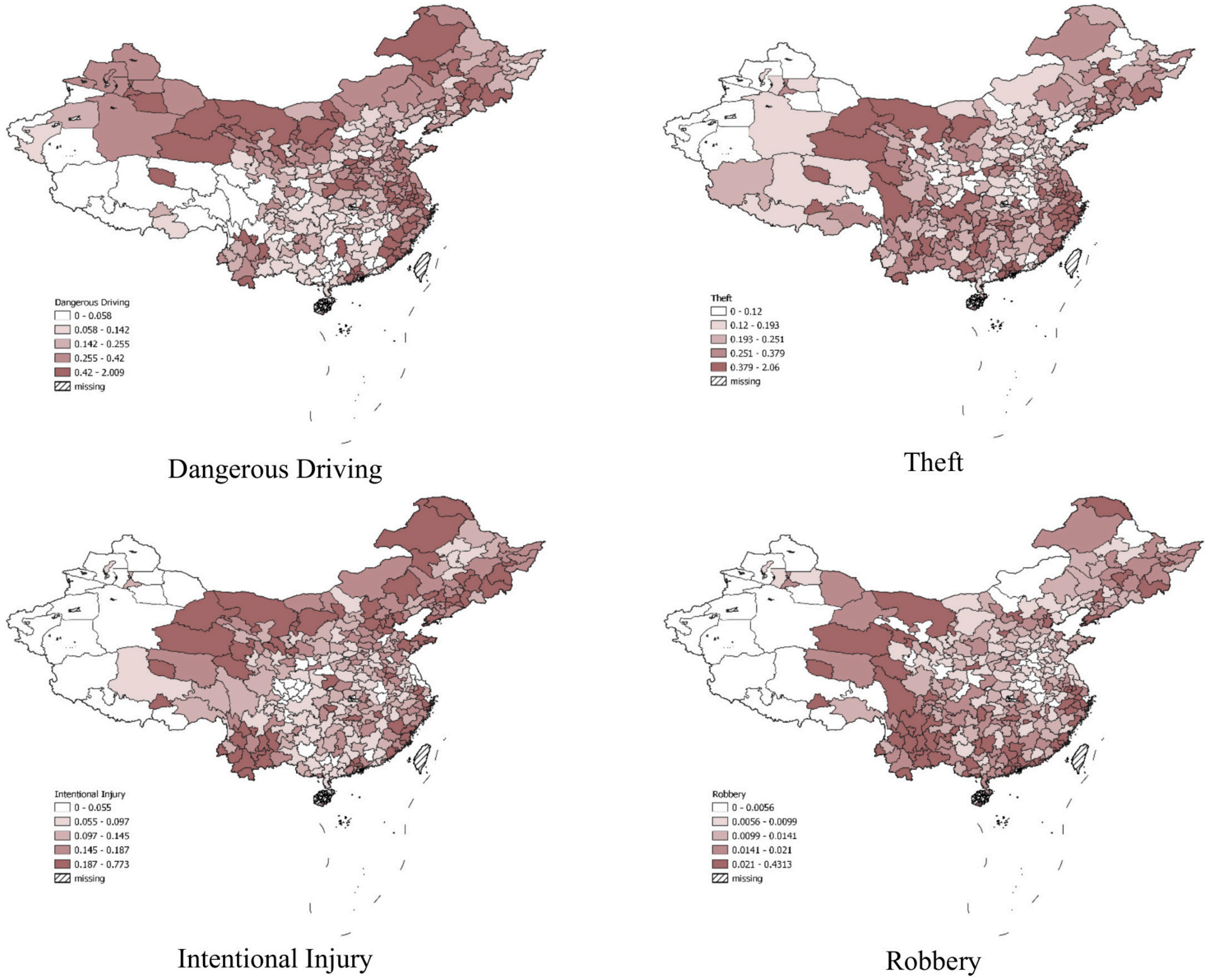


Fig. 1. Geographical distribution of crime rates.
Notes. This figure presents the geographical distribution of crime rates for different crimes. The crime rates are calculated using the number of the corresponding crimes divided by the population of each city that year.

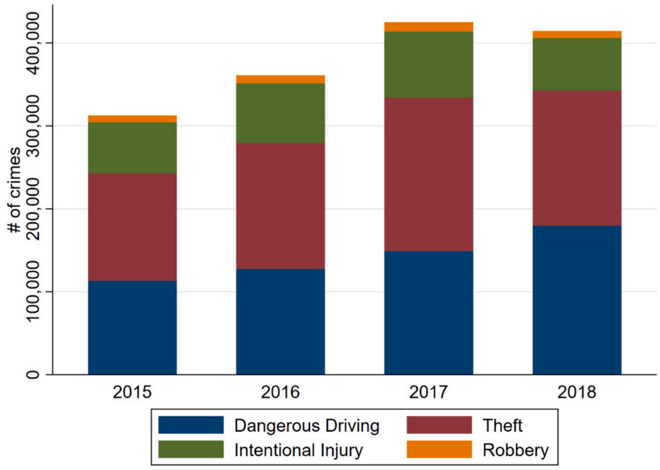


Fig. 2. Time trends of different crimes, by year.
Notes. This figure plots the number of different crimes per year.

Table 1
Summary statistics (2015–2018, 336 cities).

	N	Mean	SD	Min	Max
Panel A: crime rate (the # of crimes/population in one million)					
Dangerous Driving	481,398	0.304	0.723	0	168.251
Theft	481,398	0.305	0.743	0	38.600
Intentional Injury	481,398	0.144	0.417	0	40.092
Robbery	481,398	0.019	0.153	0	24.125
Panel B: case characteristics (case level)					
Voluntary Surrender	1,521,000	0.205	0.404	0	1
First Offender	1,521,000	0.129	0.336	0	1
Accomplice	1,521,000	0.004	0.066	0	1
Arm	1,501,000	0.068	0.252	0	1
Imprisonment <1 yr	1,501,000	0.801	0.399	0	1
Imprisonment in [1,5) yrs	1,501,000	0.174	0.379	0	1
Imprisonment $\geq$ 5 yrs	1,501,000	0.025	0.156	0	1
Panel C: criminal characteristics (criminal level)					
Age $\leq$ 25	913,960	0.178	0.383	0	1
Age in [25,35)	913,960	0.409	0.492	0	1
Age in [35,45)	913,960	0.325	0.468	0	1
Age $\geq$ 45	913,960	0.089	0.284	0	1
Female	1,277,000	0.047	0.212	0	1
Male	1,277,000	0.953	0.212	0	1
Panel D: pollution and atmospheric conditions					
$PM_{2.5}$ ($\mu g/m^3$)	484,862	44.726	38.226	1.500	1787.583
Wind Speed (m/s)	489,827	2.170	1.085	0	14.100
Temperature (°C)	489,876	14.154	11.212	−36.750	42.300
Precipitation (mm)	486,848	2.820	9.452	0	1529.900
Sunshine Duration (h)	483,566	5.502	4.028	0	19
Atmospheric Pressure (hPa)	489,870	948.044	88.525	552.670	1048.900
Thermal Inversion (°C)	489,435	−1.228	1.266	−8.762	7.903

Notes. All the statistics are reported at the city-date level during the sample period 2015–2018. Panel A reports summary statistics of the daily crime rates per city for different crimes, rates of cases involving voluntary surrender, first offender, and accomplice, as well as the crime rates of different populations in the sample. All the variables in Panel A are calculated using the corresponding number of cases divided by the population (one million as the unit) of the city in that year. Panel B presents pollution and atmospheric conditions. *Thermal inversion strength* is defined as the temperature difference between the above-ground and ground temperature, with a positive value indicating the existence of thermal inversion.

document. Panel C of Table 1 shows that the majority of criminals are between the ages of 25 and 35, making up 40.9%. The remaining offenders are divided between those aged 35–45 (32.5%), under 25 (18.6%), and over 45 (7.9%). The vast majority of criminal offenders are male, accounting for 95.3%.

Panel B presents the summary statistics for our key dependent variable and other control variables—pollution and atmospheric conditions—at the city-daily level. It is worthwhile to note that there are substantial variations in pollution levels and as well as in weather conditions. During our study period from 2015 to 2018, the nationwide city-daily average concentration of $PM_{2.5}$ was 45 μg/m^3 (with a standard deviation of 38 μg/m^3), much higher than the primary annual $PM_{2.5}$ standard set by the U.S. Environmental Protection Agency (EPA) at 12 μg/m^3 and the China's Ministry of Ecology and Environment (MEE) at 15 μg/m^3.[5] As for our instrumental variable, the average value of thermal inversion strength is negative (−1.23), suggesting that under normal circumstances, the above-ground temperature is lower than the ground temperature. Specifically, 11.2% of our city-day sample experienced thermal inversions.

3. Empirical strategy

There are several identification challenges for inferring a causal link between pollution and crime. The prime concern is the possible presence of unobserved correlated factors. For example, if pollution is higher in areas with more intensive economic activities, a naive OLS estimate might understate the effect of pollution on crime, as crime may be lower in those areas for other correlated reasons (e.g., higher quality of education). We overcome this and other related econometric challenges by first controlling for a full set of fixed effects, and then utilizing the instrumental variable approach.

3.1. Panel fixed effect model

The national level long panel data allows us to control for a full set of fixed effects to best address potential endogeneity concerns. We first estimate the fixed effect model of the following form:

$$Y_{it} = \delta_0 + \delta_1 P_{it} + \delta_2 X_{it} + \lambda_t + \delta_{it(year,month)} + \varepsilon_{it} \tag{1}$$

where Y_{it} is the crime rate (measured as the number of crimes divided by million population) in city i on date t, and P_{it} is the corresponding air pollution measured by $PM_{2.5}$. X_{it}, denotes a set of control variables to account for time-varying local weather conditions that may influence criminal activity, including temperature, wind speed, precipitation, sunshine duration, and atmospheric pressure. Temperature is widely documented to affect aggressive behaviors and conflicts (Dell et al., 2014; Ranson, 2014), and other weather conditions such as sunshine duration and precipitation are also relevant to the conduct of criminal activities (Doleac & Sanders, 2015; Tealde, 2022). We also control for high-dimensional fixed effects: λ_t denotes a series of time fixed effects including year-month, day-of-month, day-of-week, and holiday fixed effects[6] to account for the potential periodic co-movement between pollution and crime unrelated to the causal effect of pollution. For example, there may be higher people mobility and thus more potential victims on weekends compared to weekdays, and the pollution level may also be higher on weekends due to the higher mobility level; this correlation may upward bias our estimation on the causal effect of pollution on crime. This effect is captured by the day-of-week fixed effect. $\delta_{it(year,month)}$ denotes city-by-year and city-by-month fixed effects to absorb annual and seasonal city characteristics that may be correlated with pollution levels. Lastly, it is worth noting that we employ a weighted OLS regression using the total population of each city in each year as weights to correct for the sampling weights. To allow for serial and spatial correlation in pollution and criminal activities, all standard errors are two-way clustered at the city and date level.

3.2. Instrumental variable approach

Although the exploiting fixed effect strategy in conjunction with the range of control variables, air pollution levels are not randomly assigned; therefore, we cannot conclusively rule out the presence of unobserved time-varying correlated factors. Furthermore, the above model may be susceptible to reverse causality[7] and measurement error which may also bias our results. For example, criminal activities may be negatively correlated with unobservable economic activities, whereas pollution is positively correlated with unobservable economic activities. If unobservable economic activities are omitted, this could lead to an underestimation of the true effects of pollution. We therefore complement our main empirical strategy with an instrumental variable approach which relies on changes in thermal inversion as exogenous shocks to local air pollution concentrations. More formally, we estimate the following 2SLS model:

$$\text{1st stage}: P_{it} = \alpha_0 + \alpha_1 TI_{it} + \alpha_2 X_{it} + \lambda_t + \delta_{it(year,month)} + \epsilon_{it} \tag{2}$$

[5] The U.S. EPA has established two levels of National Ambient Air Quality Standards (NAAQS) for $PM_{2.5}$, with the primary standard set at 12.0 μg/m^3 and the secondary standard at 15.0 μg/m^3 (as seen at https://www.epa.gov/pm-pollution/national-ambient-air-quality-standards-naaqs-pm#:~:text=Currently%2C%20EPA%20has%20primary%20and,150%20%C2%B5g%2 fm3)., accessed on February 8, 2023 Molitor et al., 2023). China MEE has set the primary annual $PM_{2.5}$ standard of 15 μg/m^3 and secondary standard of 35 μg/m^3, (as seen in the Ambient Air Quality Standards released by MEE: https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/dqhjbh/dqhjzlbz/201203/W020120410330232398521.pdf, accessed on February 8, 2023 Molitor et al., 2023).

[6] Holidays refer to legally designated national holidays, including New Year's Day, Chinese New Year, Tomb Sweeping Day, Labor Day, Dragon Boat Festival, Mid-Autumn Festival, and National Day.

[7] A reverse causality is possible if more crime affects pollution by affecting people's mobility and thus the traffic flow.

$$2\text{nd stage}: Y_{it} = \delta_0 + \delta_1 \widehat{P_{it}} + \delta_2 X_{it} + \lambda_t + \delta_{it(year,month)} + \varepsilon_{it}. \tag{3}$$

where TI_{it} denotes the instrumental variable, thermal inversion strength, calculated using the temperature difference between the above-ground and ground temperature in city *i* on date *t*. Thermal inversion is a common meteorological phenomenon that leads to higher concentrations of pollutants near the ground. It has been widely used as the instrumental variable to study the causal effects of air pollution on both long-term and short-term consequences such as infant and adult mortality, labor productivity, student performance, and migration (Chen, Oliva, & Zhang, 2022; Fu et al., 2021). In normal cases, temperature decreases as altitude increases, so pollutants can circulate vertically from lower to higher altitudes, thus decreasing air pollution concentration near the ground. However, a thermal inversion occurs when a mass of hot air gets caught above a mass of cold air, trapping pollutants (Arceo et al., 2016). Conditional on temperature and other weather conditions, inversions themselves do not correlate with criminal activities other than through the accumulation of pollutants; therefore, thermal inversions are a useful source of exogeneous variation. All other variables are defined as in part A.

4. Main findings

We first present our main results based on the fixed effect model and the instrumental variable approach, with the crime rate for different types of criminal offenses as the dependent variable. We then allow for the non-linear effect of air pollution on the crime rate in our main specification. Lastly, we exploit the rich case level and defendant level information in our dataset and present several heterogeneity analyses.

4.1. Baseline results

Table 2 Panel A reports the baseline results as specified in Eq. (1). Columns (2)–(5) report the results with the crime rates for dangerous driving, theft, intentional injury, and robbery as the dependent variable, respectively. The coefficient estimate in column (4) suggests that an increase of daily $PM_{2.5}$ by 10 $\mu g/m^3$ (corresponding to 25% of a standard deviation in our sample) is associated with an increase in the daily crime rate of intentional injury by 0.204%. Columns (2), (3), and (5) suggest that air pollution has no statistically significant effect on dangerous driving, theft, or robbery.

Table 2 Panel B reports 2SLS estimates from the instrumental variable (IV) strategy, which is our preferred specification. Column (1) reports the first stage of the 2SLS results. It shows that thermal inversion is positively correlated with $PM_{2.5}$ as expected, and the effect is statistically significant at the 1% level. The KP-F statistics exceed 250, confirming that our IV is powerful. The 2SLS estimates are larger in magnitude than the OLS estimates as we expected because the IV eliminates the endogeneity problem (thus the underestimation bias discussed in Section 3.2). Besides, Bondy et al. (2020) and Herrnstadt et al. (2021) also find higher estimates when using the IV strategy. This increase in the size of the coefficient occurs because IVs can only retrieve local average treatment effects. Fig. A.1 shows box plots for the raw and IV-fitted values of $PM_{2.5}$. As expected, the IV strategy shrinks the value of the $PM_{2.5}$ at the extremes of the distribution, with potential relevant effects in the interpretation of point estimates (Chen & Liu, 2013). Column (4) suggests that an increase in daily $PM_{2.5}$ by 10 $\mu g/m^3$ (corresponding to 25% of a standard deviation in our sample) leads to an increase in the daily crime rate of intentional injury by 1.583%. Columns (2), (3) and (5) suggest that air pollution is negatively correlated with the crime rate of dangerous driving, and positively correlated with that of theft and robbery; though the estimated coefficients are statistically insignificant. This estimate is economically significant and suggests that the average daily crime rate in an average city in China is 28.274% higher on the most polluted days ($PM_{2.5} = 178.758$) compared to days with the lowest level of pollution ($PM_{2.5} = 0.150$).

It is worth noting that our findings corroborate findings in the literature that in developed countries, air pollution only affects crimes that are more likely to be spontaneous (intentional injury), but do not affect premeditated crimes that involve planning (robbery and theft) (Bondy et al., 2020). Table A.1 provides explanatory definitions of different criminal charges in the Criminal Law of the People's Republic of China. Intentional injury is more likely to be an impulsive act without premeditation, whereas theft, and robbery are more likely to be pre-determined and premeditated crimes.[8] Dangerous driving may or may not be premeditated, depending on the cause.[9]

In addition, regarding the magnitudes of the coefficients, we compare our estimates with those in other studies and find ours are comparable with previous findings. Table A.2 presents the summary of estimated air pollution impacts in the literature. Specifically,

[8] According to the Article 234 of Criminal Law of the People's Republic of China, the crime of intentional injury refers to the intentional act of illegally damaging the physical health of another person. There are various methods for committing intentional injury, and the method used by the perpetrator does not affect the constitution of the crime. Sentencing for the crime of intentional injury is classified into three levels, depending on whether it causes serious injury or death. Overall, the crime of intentional injury is a violent crime, usually including assault and battery.

[9] According to the Article 133(I) of Criminal Law of the People's Republic of China, whoever drives a motor vehicle on a road under any of the following circumstances shall be sentenced to criminal detention in addition to a fine: (1) Racing a motor vehicle on a road with execrable circumstances. (2) Driving a motor vehicle on a road while intoxicated. (3) Engaging in the school bus business or passenger transport and carrying passengers by loading much more than the fixed number of passengers, or driving the vehicle by seriously exceeding the prescribed speed. (4) Transporting any hazardous chemical in violation of the provisions on the safety administration of hazardous chemicals, which endangers public safety.

Table 2
Effect of $PM_{2.5}$ on crime rates.

	(1)	(2)	(3)	(4)	(5)
	$PM_{2.5}$	Dangerous Driving	Theft	Intentional Injury	Robbery
Panel A: OLS					
$PM_{2.5}$ (10 as the unit)		−0.0003	0.0005	0.0003**	−0.0000001
	/	(0.0004)	(0.0004)	(0.0001)	(0.00005)
Relative effect		−0.110	0.171	0.204	−0.001
Panel B: 2SLS					
1st stage					
Thermal Inversion	1.0494***				
	(0.0657)				
2nd stage					
$PM_{2.5}$ (10 as the unit)		−0.0004	0.0039	0.0023***	0.0001
		(0.0013)	(0.0032)	(0.0007)	(0.0003)
Relative effect	/	−0.147	1.300	1.583	0.544
KP-F statistics		254.747	254.747	254.747	254.747
Benchmark		0.303	0.303	0.144	0.019
Observations	462,268	462,268	462,268	462,268	462,268
Atmospheric conditions	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date	City Date

Notes. This table presents the impacts of air pollution on different crimes. Panel A reports the OLS estimates of eqs. (1), and Panel B reports the 2SLS estimates of eqs. (2) and (3). Column (1) of Panel B presents the 1st stage results. $PM_{2.5}$ is scaled by 1/10 and its coefficient represents the impact of per 10-unit $PM_{2.5}$. The dependent variables from columns (2) to (5) are the crime rates of the corresponding crimes. All regressions control for atmospheric conditions consisting of temperature, wind speed, precipitation, sunshine, and atmospheric pressure. The regressions are weighted using the total population (one million as the unit) of each city that year. *Benchmark* is the average of the dependent variable, and the *relative effect (%)* is the ratio of the estimated coefficient and *benchmark*. Standard errors in parentheses are robustly two-way clustered at the city and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

we observe a 1.583% increase in intentional injuries for every 10-unit increment in $PM_{2.5}$, or alternatively, 1.3% increase for every 10-unit rise in AQI (to be presented in subsequent Table 4). Burkhardt et al. (2019), using fixed-effects panel models with U.S. crime statistics, show that a 10% increase in PM_{10} (with an average level of 9.95 μg/m^3) increases violent crimes by 0.14%, across a sample of U.S. counties. This could be translated to an approximately 1.407% (=10/(9.95*10%)*0.14%) increase for every 10-unit increase in PM_{10}. Bondy et al. (2020) use PPML estimator panel models and find that a 10-unit rise in AQI increases crimes by 1.7% in London. Sarmiento (2023) finds an additional 10 units of NowCast AQI results in a 0.33% and 0.48% hourly crime rate escalation in Mexico City and New York, respectively. Zarate Barrera (2021) finds a 1.11% rise in crime for every 10-unit increment in AQI in Mexico City. Our results manifest an alignment with earlier findings.

Whilst we believe that our above empirical strategy yields credible evidence on the causal link between air pollution and crime, we cannot conclusively rule out the "supply" side effect of air pollution on crime. From the "supply" side, air pollution may have a negative effect on human mobility, which means that potential victims are less likely to go out on polluted days. The decrease in potential victims' mobility increases the potential criminals' "search cost" and reduces the likelihood of a successful crime. Thus, it is reasonable to argue that our estimates above provide a lower-bound estimate for the effect of air pollution on crime.

Another concern is that these findings potentially reflect the behavior of police instead of criminals. Police may be more aggressive on polluted days, leading to an increased likelihood of apprehending criminals. However, if this were the case, we would expect similar results for different types of criminal cases, rather than only for those involving violence such as intentional injury. One way to distinguish between the effects of air pollution on police behavior and those on perpetrator behavior is to compare the effects of pollution on arrest rates and reported crime rates. Unfortunately, we do not have data on reported crimes, limiting our ability to draw definitive conclusions regarding the role of police behavior. Despite the lack of direct evidence in our study, a study by Behrer and Bolotnyy (2022) offers valuable insights. They find the increase in arrests on extreme hot days is driven by increases in violent crime rather than by changes in police behavior, utilizing the difference between reported crimes and arrests. Additionally, Singh and Visaria (2021) find no changes in effort exerted by the police on days of high air pollution by examine the relationship between the number of arrests and air pollution, in the context of India. These findings may provide some insight into this matter.

In addition, to further mitigate this concern related to measurement issues, we follow a strand of the economics literature that uses internet search intensity to proxy public interest in, and perceptions of socioeconomic conditions (Kearney & Levine, 2015; Ma et al., 2025; Madestam et al., 2013). Specifically, we use the Baidu index for crime-related keywords as a measure of individuals' perceptions of local security. Following Ma et al. (2025), we regress these crime-related Baidu search indices on air pollution as a robustness check (see Table A.3). Column (1) uses the aggregate Baidu Index constructed as the sum of four general crime-related keywords,[10] while columns (2) to (5) report results for each corresponding keyword. The results show that air pollution increases search indices for crime-related keywords, consistent with our baseline results.

4.2. Nonlinearity

We then examine the possible nonlinear relationship between pollution and crime by substituting our continuous $PM_{2.5}$ measure with dummy variables for different levels of pollution. Studies have shown that individuals react disproportionally stronger as air pollution increases (Aragón et al., 2017; Bondy et al., 2020; Dong et al., 2021). Following the literature, we decompose the continuous $PM_{2.5}$ into six categories ([0,10), [10,35), [35,75), [75,150), [150,200), and [200,+∞), respectively). We assign each category a dummy variable, leave the first dummy as the reference group, and include the last five in the regression. As shown in Table 3, the effect of pollution on intentional injury increases significantly with the level of exposure—confirming the nonlinear effect of pollution on violent crimes. Specifically, column (3) shows that compared to the base group ($PM_{2.5}$ less than 10 μg/m^3), the effect of $PM_{2.5}$ on crime rates of intentional injury will increase by 1.4% (=0.0060/0.144) if $PM_{2.5}$ increases to above 10, by 4.4% (=0.0063/0.144) if $PM_{2.5}$ increases to above 35, by 6% (=0.0086/0.144) if $PM_{2.5}$ increases to above 75, by 7.6% (=0.0110/0.144) if $PM_{2.5}$ increases to above 150, and by 8.1% (=0.0117/0.144) if the $PM_{2.5}$ is more than 200 μg/m^3.[11] Column (1) suggests that the effect of pollution on dangerous driving is consistently negative and the effect becomes statistically significant at the 10% level when the level of $PM_{2.5}$ exceeds 150. This is probably because individuals decrease driving activities and become more cautious about driving on high-pollution days, which reduces dangerous driving crime. Column (2) suggests that the effect of pollution on theft is consistently positive but statistically insignificant. Lastly, while pollution on average has no statistically significant effect on robbery, column (4) suggests that the effect becomes statistically significantly positive when the level of $PM_{2.5}$ exceeds 150—an increase in daily $PM_{2.5}$ by 10 μg/m^3 leads to the daily crime rate of robbery increase by 19.5% (=0.0037/0.019). It is worth noting that in an average year, 45 cities (out of 336 cities) have more than 30 days with $PM_{2.5}$ over 150, further intensifying concerns for an even more severe effect on crime.

Table 3
Nonlinear effects of $PM_{2.5}$ on crime rates.

	(1) Dangerous Driving	(2) Theft	(3) Intentional Injury	(4) Robbery
$PM_{2.5}$ in [10, 35)	−0.0124	0.0206	0.0060**	0.0013
	(0.0095)	(0.0163)	(0.0030)	(0.0013)
$PM_{2.5}$ in [35, 75)	−0.0108	0.0259	0.0063**	0.0017
	(0.0103)	(0.0178)	(0.0031)	(0.0013)
$PM_{2.5}$ in [75, 150)	−0.0114	0.0310	0.0086***	0.0017
	(0.0115)	(0.0197)	(0.0033)	(0.0014)
$PM_{2.5}$ in [150, 200)	−0.0218*	0.0351	0.0110***	0.0037**
	(0.0130)	(0.0229)	(0.0041)	(0.0019)
$PM_{2.5}$ in [200,.)	−0.0236	0.0229	0.0117**	0.0014
	(0.0148)	(0.0240)	(0.0046)	(0.0020)
Observations	469,543	469,543	469,543	469,543
R-squared	0.336	0.424	0.099	0.070
Benchmark	0.304	0.304	0.144	0.019
Atmospheric conditions	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date

Notes. This table presents the nonlinear relationship between air pollution and different crimes. The dependent variables from columns (1) to (4) are the crime rates of the corresponding crimes. The omitted bin is the bin indicating $PM_{2.5}$ less than 10. Standard errors in parentheses are robustly two-way clustered at the city and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[10] The keywords are *criminal activities* ("犯罪活动" in Chinese), *maintaining stability* ("维稳" in Chinese), *law and order* ("治安" in Chinese), and *public security* ("公共安全" in Chinese).

[11] Burkhardt et al. (2019) find in U.S., the effect of $PM_{2.5}$ on violent crimes increase until 20 μg/m^3 but remains constant shortly thereafter. Specifically, violent crime increases by about 1.04% if $PM_{2.5}$ is 20 μg/m^3 relative to 0 μg/m^3, similar to our estimate 1.4% when $PM_{2.5}$ falls in the bin [10,35) μg/m^3 compared to $PM_{2.5}$ less than 10 μg/m^3. Our study greatly extends the external validity of the effects of pollution on crime given the fact that the pollution levels in developed countries are typically much lower than that in developing countries.

4.3. Robustness

Table 4 presents the results of several robustness checks. We first flexibly control the atmospheric conditions by controlling both the linear and quadratic forms of atmospheric conditions. Panel A shows that the magnitude and statistical significance of the estimates are similar to the baseline results (1.475% versus 1.583%).

Second, we examine the robustness of our results with different instrument variables. In the baseline specification, we use the thermal inversion strength (the temperature difference between above-ground and ground temperature) as the instrument variable. To ensure our results are not sensitive to the choice of instrument variable, we further use an alternative instrument variable, the number

Table 4
Robustness checks using other specifications.

	(1)	(2)	(3)	(4)
	Dangerous Driving	Theft	Intentional Injury	Robbery
Panel A: linear and quadratic forms of weather				
$PM_{2.5}$ (10 as the unit)	−0.0014	0.0034	0.0021***	0.0001
	(0.0013)	(0.0032)	(0.0007)	(0.0003)
Relative effect (%)	−0.455	1.132	1.475	0.372
KP-F statistics	254.905	254.905	254.905	254.905
Panel B: the number of thermal inversions as the instrument				
$PM_{2.5}$ (10 as the unit)	0.0002	0.0038	0.0020***	0.0001
	(0.0012)	(0.0029)	(0.0006)	(0.0003)
Relative effect (%)	−0.455	1.132	1.475	0.372
KP-F statistics	265.339	265.339	265.339	265.339
Benchmark	0.303	0.303	0.144	0.019
Panel C: arcsinh(# of crimes) as the dependent variable				
$PM_{2.5}$ (10 as the unit)	0.0005	0.0036	0.0069***	0.0012
	(0.0028)	(0.0025)	(0.0024)	(0.0011)
Relative (marginal) effect (%)	0.120	0.893	1.112	0.029
KP-F statistics	254.747	254.747	254.747	254.747
Mean of arcsinh(# of crimes)	0.654	0.660	0.385	0.055
Mean of $PM_{2.5}/10$	4.472	4.472	4.472	4.472
Observations	462,268	462,268	462,268	462,268
Panel D: AQI as the independent variable				
AQI (10 as the unit)	−0.0004	0.0032	0.0019***	0.0001
	(0.0011)	(0.0026)	(0.0006)	(0.0002)
Relative effect (%)	−0.121	1.070	1.303	0.448
KP-F statistics	305.651	305.651	305.651	305.651
Benchmark	0.302	0.303	0.144	0.019
Observations	462,311	462,311	462,311	462,311
Atmospheric conditions	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes

Notes. This table presents the 2SLS estimates for the robustness checks. We control for linear and quadratic forms of weather in Panel A, use the number of thermal inversion occurrences as an alternative instrument in Panel B, use inverse hyperbolic sine transformation for the number of crimes (i.e., ln{y + sqrt(y*y + 1)}) as an alternative dependent variable in Panel C, and use AQI as an alternative independent variable in Panel D. $PM_{2.5}$ (AQI) is scaled by 1/10 and its coefficient represents the impact of per 10-unit $PM_{2.5}$ (AQI). The dependent variables from columns (1) to (4) in Panel A, B, and D are the crime rates of the corresponding crimes. The regressions are weighted using the total population (one million as the unit) of each city that year. *Benchmark* is the average of the dependent variable, and the *relative effect (%)* in Panel A, B, and D is the ratio of the estimated coefficient and *benchmark*. The relative (marginal) effect in Panel C is is obtained by multiplying the estimated coefficient with the mean of the independent variable and dividing the product by the square root of 1 plus the reciprocal of the square of the mean of the dependent variable (i.e., _b[$PM_{2.5}$]*mean[$PM_{2.5}$]/sqrt(1 + 1/ihs(crime)^2)). Standard errors in parentheses are robustly two-way clustered at the city and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of thermal inversion occurrences per city per day. The data sensor observes temperatures four times a day, and thus the number of thermal inversion appearances ranges from zero to four. On average, there are 0.79 times thermal inversions per city per day. We find very similar results with this different definition of the instrument variable (1.475% versus 1.583%).

Third, to ensure our results are not sensitive to the choice of dependent variable, we use inverse hyperbolic sine of the number of criminal cases as an alternative one.[12] We find similar relative effects to the baseline results (1.112% versus 1.583%). Fourth, we also use an alternative independent variable, AQI, which is a composite index that incorporates several pollutants including $PM_{2.5}$, SO_2, NO, CO and O_3. We find similar results (1.303% versus 1.583%) because AQI and $PM_{2.5}$ are highly correlated in China between 2015 and 2018.

In addition, we examine whether our findings are sensitive to different fixed effects. As shown in Table A.7, the results are consistent across different specifications. We further utilize PPML estimation with the number of crimes as the dependent variable. Unlike the traditional Poisson estimation, PPML does not require the conditional variance to be equal to the conditional mean. In Table A.8, the estimated coefficient of $PM_{2.5}$ for intentional injury is 0.0025, with statistical significance at the 5% level. The estimates indicate that an additional 10 units of daily $PM_{2.5}$ leads to a 0.25% increase in intentional injury cases. The PPML results closely align with the baseline results, except for theft where PPML estimates show a positive significant effect. However, it's important to acknowledge the endogeneity of $PM_{2.5}$ in the PPML estimation. Given the endogeneity in $PM_{2.5}$, we prefer to use a linear model with instrument variable as the baseline specification.

4.4. Heterogeneity

One of the main advantages of our crime data is that it contains detailed information on the characteristics of the criminal cases and of the defendants. We leverage this detailed information and examine the heterogonous effect of air pollution on crime, which provides a deeper decomposition of our results and facilitates understanding of the mechanism by which air pollution affects potential criminals' behavior. As our primary findings mainly document the effect of air pollution on intentional injury, we focus on the heterogeneous effect on this type of crime in this section. Here, we present heterogeneity in city and offender characteristics and discuss more detailed case-level heterogeneity in Section 5.

First, we extract the detailed address and/or location where the criminal action took place. By searching for the keywords that can identify indoor and outdoor crimes, we classify all intentional injury cases as occurring either indoors or outdoors. However, due to the irregularity of the textual data and the fact that a significant proportion of the legal documents do not mention the specific locations where the crimes were committed, we were only able to identify the crime location for 441,257 cases (out of 1,513,377), 92,410 of which were indoor crimes and 348,847 of which were outdoor crimes. While we do not directly observe the difference in indoor pollution level and outdoor pollution level separately, indoor air pollution levels are generally lower than outside levels. If individuals spend more time in their home when air pollution levels are elevated, we expect to see increased indoor violent crimes, which may indicate an increase in domestic violence. Alternatively, due to the difference between the outdoor and indoor pollution levels, we may expect a larger effect of pollution on outdoor crimes. Table A.4 reports the regression results using our baseline IV specification as specified in Eqs. (2) and (3). The results suggest that our results are mainly driven by the outdoor crime sample, and we find no statistically significant effect of air pollution on the indoor crime rate.

We then investigate the heterogeneous effect of air pollution across cities with different city-level characteristics, focusing on governance capacity, education level, economic development, and living-cost pressure. Specifically, we use local fiscal revenue from city-level statistical yearbooks as a proxy for governance capacity, and city-level average years of schooling from the 2015 Population Census to measure education levels, following Cameron et al. (2019). We separate the sample cities into two subsamples using the median value of each indicator and estimate the baseline specification separately for each subgroup. As shown in Table 5 Panel A, the effect of $PM_{2.5}$ on intentional injury rates is significantly larger in cities with lower fiscal revenue and lower education levels, based on Fisher's permutation test. To further explore the roles of economic development and living-cost pressure, we divide cities into four groups based on the median values of GDP and the housing price-to-income ratio (HPIR). The results in Table 5 indicate that the pollution effect is most pronounced in cities with low GDP but high housing price-to-income ratios (HPIR), where a 10-unit increase in $PM_{2.5}$ raises intentional injury crime rates by over 6% relative to the baseline. In contrast, the pollution effect is muted in economically developed cities facing high housing pressure. One plausible explanation is that high-income cities, despite elevated housing costs, tend to have stronger governance capacity, more extensive public services, and better social and institutional buffers, which can diminish the translation of short-term pollution-induced stress into criminal behavior. In addition, we explore additional heterogeneity by unemployment, GDP per capita, and population. As reported in Table A.5, the pollution effect is slightly larger (and marginally statistically significant) among cities with lower GDP per capita and smaller populations.

At the individual criminal level, we identify the offenders' age and gender. For age, we divide the criminals into four age groups ([18, 25), [25,35), [35,45), and [45,100), respectively). Table 6 reports the regression results for each category. Columns (1)–(4) suggest that our results are mainly driven by the cohort age of 25–35; while the effect of pollution on crime in other age groups is also positive, it is statistically insignificant. It is probable that young individuals, who may be less able to control their emotions, possess greater awareness of air quality than their older counterparts. In part this may be due to the widespread use of smartphones and the

[12] Specifically, this measure is obtained by applying the formula ln{y + sqrt(y*y + 1)}, with y denoting the number of criminal cases. The marginal effect is obtained by multiplying the estimated coefficient with the mean of the independent variable and dividing the product by the square root of 1 plus the reciprocal of the square of the mean of the dependent variable.

Table 5
City heterogeneity in $PM_{2.5}$ effects on intentional injury.

Dep. Var.	(1)	(2)	(3)	(4)
	Intentional Injury Rate			
Panel A. Governance capacity and education level				
Group	Fiscal Revenue Low	 High	Years of Education Low	 High
$PM_{2.5}$ (10 as the unit)	0.0037**	0.0017**	0.0030***	0.0013
	(0.0014)	(0.0008)	(0.0010)	(0.0010)
Coef. Diff.	0.0020**		0.0017**	
p-value	0.033		0.033	
Observations	225,095	236,094	256,357	205,911
Relative effect	2.706	1.147	2.093	0.869
Benchmark	0.136	0.151	0.143	0.144
KP-F Stat.	203.700	184.708	160.800	144.343
Panel B. Economic development and living pressure				
Group	Low HPIR Low GDP	Low HPIR High GDP	High HPIR Low GDP	High HPIR High GDP
$PM_{2.5}$ (10 as the unit)	0.0029*	0.0042***	0.0077**	0.0010
	(0.0016)	(0.0016)	(0.0036)	(0.0009)
Coef. Diff. Btw. Col (4)	0.0019*	0.0031*	0.0067***	/
p-value	0.100	0.067	0.000	/
Observations	102,643	80,739	46,057	138,714
Relative effect	2.109	3.242	6.130	0.624
Benchmark	0.139	0.128	0.126	0.163
KP-F Stat.	201.659	113.500	102.000	137.000
Atmospheric conditions	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date

Notes. This table examines city-level heterogeneity in the effect of air pollution on intentional injury rates, estimated using 2SLS. Panel A explores the heterogeneity by governance capacity and education level. Cities are divided into high- and low-fiscal-revenue groups and high- and low-education groups based on whether city-level fiscal revenue and average years of education are above or below the sample median, respectively. "Coef. Diff." reports the difference in the estimated $PM_{2.5}$ coefficient between the high and low groups within each dimension. Panel B examines the heterogeneity by economic development and living pressure. Cities are classified into high- and low-HPIR groups and further split by whether GDP is above or below the sample median. "Coef. Diff. Btw. Col (4)" reports the difference in the estimated $PM_{2.5}$ coefficient between each column and column (4). Statistical significance of coefficient differences is assessed using Fisher's permutation tests, with *p*-values obtained via bootstrapping. "Relative effect" reports the percentage change relative to the mean of the dependent variable ("Benchmark"). All specifications are the same as baseline. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Internet among younger individuals, which allows them to pay more attention to air pollution. Columns (5)–(6) suggest that males are more likely to be affected by pollution compared to females. Considering the relatively high proportion of zeros in the dependent variables in heterogeneity analysis, which may make the results sensitive to model specifications, we conduct additional robustness by re-specifying the dependent variable as a binary indicator for whether any crime of a given type occurred within a group (e.g., whether at least one intentional injury committed by a male occurred), and estimate linear IV models that focus on the extensive margin. As shown in Table A.6, the results using binary outcomes are highly consistent with Tables 6.[13] Overall, our findings are consistent with what Tu et al. (2020) find: that the young and male are more likely to change their behavior as a result of a change in awareness about pollution issues.

5. Discussion

Our primary estimates suggest that an increase in $PM_{2.5}$ on any given day has a statistically significant positive effect on violent crimes. In this section, we first conduct heterogeneity analysis to identify the most affected group, which is rarely investigated in previous literature. Next, we discuss potential mechanisms by which air pollution affects the potential criminals' behavior. We start by reconciling with the literature that pollution affects criminal behaviors that are mainly driven by irrational and emotional aggressions (Burkhardt et al., 2019). The effect on aggressive behavior can be through either physiological or psychological channels. In order to

[13] In addition, in untabulated results, estimates using PPML without instrumental variables yield similar patterns.

Table 6
Offender heterogeneity of intentional injury.

	(1)	(2)	(3)	(4)	(5)	(6)
	Age				Gender	
	<25	[25,35)	[35,45)	≥ 45	Male	Female
Panel A: OLS						
$PM_{2.5}$ (10 as the unit)	0.0001*	0.0001	0.000005	0.000001	0.0002**	0.00004*
	(0.0000)	(0.0001)	(0.00004)	(0.00002)	(0.0001)	(0.00002)
Relative effect	0.088	0.042	0.003	0.002	0.037	0.145
Panel B: 2SLS						
$PM_{2.5}$ (10 as the unit)	0.00003	0.0008**	0.0001	0.0001	0.0019***	0.00002
	(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0006)	(0.0001)
Relative effect	0.039	0.438	0.042	0.203	0.301	0.053
KP-F statistics	254.747	254.747	254.747	254.747	254.747	254.747
Observations	462,268	462,268	462,268	462,268	462,268	462,268
Benchmark	0.081	0.181	0.148	0.040	0.625	0.029
Atmospheric conditions	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date	City Date	City Date

Notes. This table presents the heterogeneity in offenders' demographics for intentional injuries. Panel A reports the OLS estimates of eq. (1), and Panel B reports the 2SLS estimates of eqs. (2) and (3). $PM_{2.5}$ is scaled by 1/10 and its coefficient represents the impact of per 10-unit $PM_{2.5}$. The dependent variables are calculated using the number of corresponding criminals divided by the city's population that year; for example, *Female* represents the percentage of female intentional injury offenders in the total population. All regressions control for atmospheric conditions consisting of temperature, wind speed, precipitation, sunshine, and atmospheric pressure. The regressions are weighted using the total population (one million as the unit) of each city that year. *Benchmark* is the average of the dependent variable, and the *relative effect (%)* is the ratio of the estimated coefficient and *benchmark*. Standard errors in parentheses are robustly two-way clustered at the city and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

further disentangle the two, we investigate the effect of ozone, which is not visible and thus can only affect one's decision through physiological channels.

5.1. Who are more vulnerable to air pollution to commit a crime?

The heterogeneities in offenders' demographics, as presented in Table 6, show that male offenders and those aged 25–35 exhibit heightened susceptibility to pollution-induced crimes. We then utilize comprehensive case- and criminal- level information to enrich this facet of the discussion. To be specific, we investigate heterogeneities in characteristics of criminal behavior (first-time offense or not, accomplice or not, armed or not), and how the offenders react after committing a crime (whether they surrender or not). The baseline results presented in Table 2 demonstrate that air pollution significantly impacts crimes that are impulsive and triggered by anger, such as intentional injury, rather than premeditated or necessity-based crimes, such as theft. Therefore, we present heterogeneity results only for intentional injury, while results for other crimes are presented in Table A.9.

Columns (1) and (2) of Table 7 show a greater effect of pollution on crime in self-surrendered cases than in non-surrender cases. Specifically, an increase of 10 $\mu g/m^3$ in $PM_{2.5}$ leads to a 2.16% increase in voluntarily surrendered intentional injury cases and a 1.078% increase in non-surrendered intentional injury cases. The results suggest that the pollution-induced perpetrators are more likely to surrender themselves after the crime. The motivation behind surrender can be either rational or moral: the criminal may be unable to withstand the subsequent consequences of their crime (such as incarceration or substantial fines), thus surrender in hope of a reduced sentence; or they may suffer a guilty conscience afterward for having committed an immoral act. Regardless of the reason for voluntary surrender, it reflects a degree of regret demonstrated by the offender, which suggests psychological factors such as emotion are at play during the crime.

Moreover, columns (3) and (4) show that air pollution has a stronger impact on intentional injury cases committed by repeat offenders (1.820% increase per 10 $\mu g/m^3$ increase in $PM_{2.5}$), compared to first-time offenders (0.758% increase per 10 $\mu g/m^3$ increase in $PM_{2.5}$, not significant). Repeat offenders have a lower mental cost for committing crime and are less stable emotionally (Dickson et al., 2013), making them more vulnerable to air pollution-induced mood changes that lead to criminal behavior. In addition, accomplice cases are more likely to be premeditated and planned previously, so we further explore the heterogeneity of accomplices and non-accomplices. Columns (5) and (6) show that intentional injury cases involving single offenders are more affected by pollution, with a 1.618% increase resulting from a 10 μg/m^3 $PM_{2.5}$ increase, which is also consistent with our hypothesis that moods are at play. To identify premeditated crimes to the greatest extent possible, we categorize all cases into those with and without weapons (considering that crimes committed with weapons are more likely to be premeditated).[14] Columns (7) and (8) show that pollution-induced intentional injuries are mainly those without weapons. Specifically, a 10 μg/m^3 $PM_{2.5}$ increase leads to a 2.149% increase in non-weapon offenses but does not affect cases involving weapons. This finding further suggests that premeditated crimes are not easily affected by air pollution, while impulsive crimes are more easily affected by air pollution. Additionally, we divided the sample into three groups based on the length of sentence as an approximation of the severity of the crime. We find that crimes with relatively less severe consequences (sentencing of less than five years) are more susceptible to air pollution impacts.

Regarding the concern related to the relatively high presence of zero outcomes in the dependent variables, similar to that in Section 4.3, we conduct additional robustness by re-specifying the dependent variable as a binary indicator for whether any crime of a given type occurred within a group (e.g., whether at least one intentional injury committed by an armed offender occurs), and estimate linear IV models that focus on the extensive margin. As shown in Table A.10, the results using binary outcomes are highly consistent with Tables 7.[15]

5.2. *Contemporaneous effect of pollution on crime—Moods as a key mechanism*

The baseline results presented in Table 2 suggest that air pollution significantly affects those crimes that are more prone to be motivated by impulsiveness and irritation, such as intentional injury, rather than those premeditated crimes and crimes committed out of need, such as theft. The heterogeneity analysis of offenders provides further evidence that pollution-induced crimes are more likely to be impulsive crimes that may be regretted afterwards. In this subsection, we include the lag terms to investigate the dynamic effect of pollution on crime.

We estimate the lag one to seven-day effects of $PM_{2.5}$ and cumulative effects over different time periods by including the pollution levels on both current day and the preceding k days in our analysis. The baseline model is specified as:

$$Y_{it} = \sum\nolimits_{\tau=0}^{k} \beta_\tau P_{i,t-\tau} + f(X_{it}) + \lambda_t + \delta_{it(year,month)} + \varepsilon_{it} \tag{4}$$

Under the above specified distributed lag model, the estimation may be biased due to the high autocorrelation among the lagged terms $P_{i,t-\tau}$, so we follow Barwick et al. (2024) and use the IV version of a flexible distributed lag model, which allows for flexible and smooth long-term effects and deals with high-autocorrelation issues. In this modified distributed lag model, β_τ, are specified as cubic B-spline functions of time with one segment:

$$\beta_\tau = \gamma_0 + \gamma_1\tau + \gamma_2\tau^2 + \gamma_3\tau^3. \tag{5}$$

The contemporaneous effect is $\beta_0 = \gamma_0$, and the effect of pollution from τ days before is $\beta_\tau = \gamma_0 + \gamma_1\tau + \gamma_2\tau^2 + \gamma_3\tau^3$. Then, we substitute β_τ into the distributed lag model and get

$$\begin{aligned} Y_{it} &= \sum\nolimits_{\tau=0}^{k} \beta_\tau P_{i,t-\tau} + f(X_{it}) + \alpha_t + \delta_{it(year,month)} + \varepsilon_{it} \\ &= \gamma_0 P_{it} + (\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3) P_{i,t-1} + \ldots + \left(\gamma_0 + \gamma_1 k + \gamma_2 k^2 + \gamma_3 k^3\right) P_{i,t-k} + f(X_{it}) + \lambda_t + \delta_{it(year,month)} + \varepsilon_{it} \\ &= \gamma_0 v_{1,it} + \gamma_1 v_{2,it} + \gamma_2 v_{3,it} + \gamma_3 v_{4,it} + f(X_{it}) + \lambda_t + \delta_{it(year,month)} + \varepsilon_{it}, \end{aligned} \tag{6}$$

where

$$\begin{aligned} v_{1,it} &= P_{it} + P_{i,t-1} + \ldots + P_{i,t-k}, v_{2,it} = P_{i,t-1} + 2P_{i,t-2} + \ldots + kP_{i,t-k}, \\ v_{3,it} &= P_{i,t-1} + 2^2 P_{i,t-2} + \ldots + k^2 P_{i,t-k}, \\ v_{4,it} &= P_{i,t-1} + 2^3 P_{i,t-2} + \ldots + k^3 P_{i,t-k}, \end{aligned} \tag{7}$$

respectively. We can then estimate the cumulative effect $\sum_{\tau=0}^{k} \beta_\tau$, which is a linear combination of $\{\gamma_i\}_{i=0}^{3}$.

The contemporaneous and lagged one to seven-day effects for each type of crime are shown in Fig. 3 Panel A, with the effects being normalized by the benchmark average for each crime. For theft and robbery, the contemporaneous effects on day 0 are positive, but not statistically significant. The lagged effects for dangerous driving, theft, and robbery remain insignificantly different from zero. As for intentional injury, the results we find in the baseline specification are mainly driven by the contemporaneous effect, the magnitude of which is very similar to what we find in the baseline estimation. High $PM_{2.5}$ four to six days prior leads to a slight increase in the crime

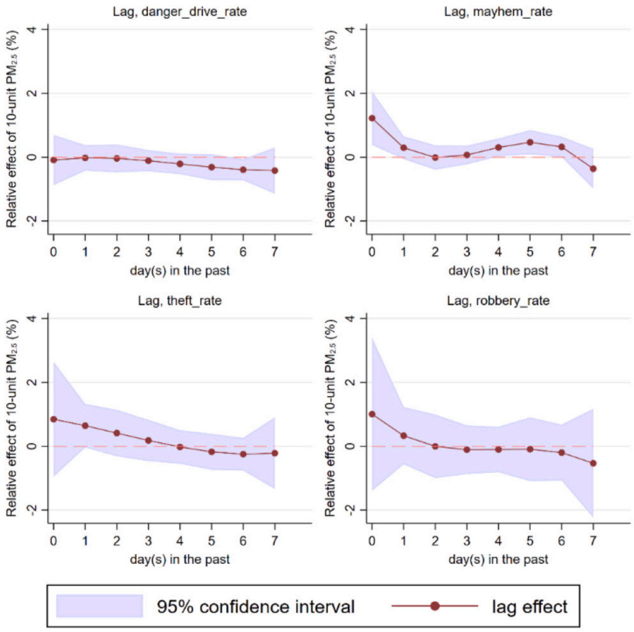
[14] If a perpetrator utilized tools such as whips, clubs, knives, steel pipes, saws, sticks, hammers, iron shovels, bricks, daggers, guns during the commission of a crime, we categorize the case as one involving weapon possession.

[15] In addition, in untabulated results, estimates using PPML without instrumental variables yield similar patterns.

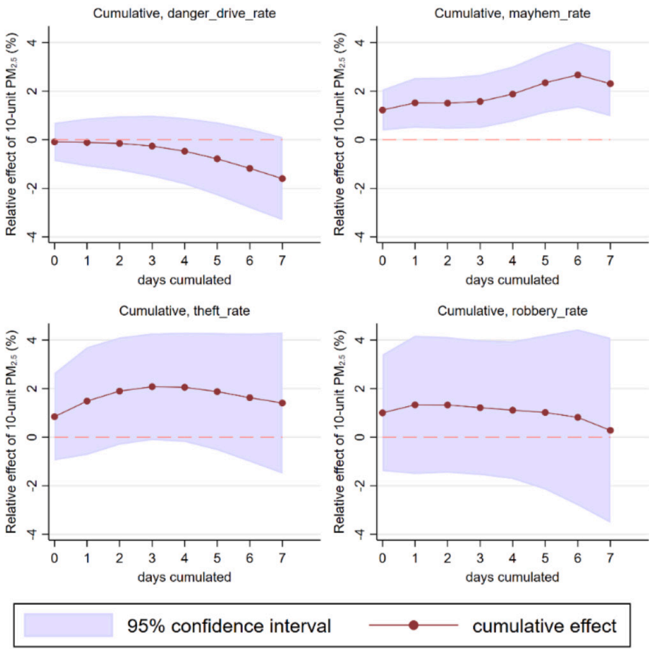
Table 7
Identifying vulnerable criminals: heterogeneity in characteristics of criminal cases for intentional injury.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Voluntary Surrender		First Offender		Accomplice		Weapon		Imprisonment		
	Y	N	Y	N	Y	N	Y	N	<1 yr	[1,5) yrs	≥ 5 yrs
Panel A: OLS											
$PM_{2.5}$ (10 as the unit)	0.0002***	0.0001	0.00002	0.0003***	0.000001	0.0003**	0.0001	0.0002**	0.0002**	0.0001	0.000005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.00002)
Relative effect	0.326	0.098	0.067	0.244	1.225	0.198	0.160	0.226	0.235	0.189	0.080
Panel B: 2SLS											
$PM_{2.5}$ (10 as the unit)	0.0014***	0.0008*	0.0002	0.0020***	−0.00004	0.0023***	0.0002	0.0021***	0.0013***	0.0010***	0.00003
	(0.0004)	(0.0004)	(0.0003)	(0.0006)	(0.0001)	(0.0007)	(0.0003)	(0.0006)	(0.0005)	(0.0004)	(0.0001)
Relative effect	2.160	1.078	0.758	1.820	−4.728	1.618	0.448	2.149	1.515	1.995	0.427
KP-F statistics	254.747	254.747	254.747	254.747	254.747	254.747	254.747	254.747	254.747	254.747	254.747
Observations	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268
Benchmark	0.067	0.077	0.032	0.112	0.001	0.143	0.048	0.096	0.086	0.048	0.006
Atmospheric conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date	City Date	City Date	City Date	City Date	City Date	City Date	City Date

Notes. This table presents the heterogeneity in case characteristics for intentional injuries. Panel A reports the OLS estimates of eq. (1), and Panel B reports the 2SLS estimates of eqs. (2) and (3). $PM_{2.5}$ is scaled by 1/10 and its coefficient represents the impact of per 10-unit $PM_{2.5}$. The dependent variables are calculated using the number of corresponding cases (Y represents yes, N represents no) divided by the city's population that year; for example, *Voluntary Surrender (Y)* denotes the percentage of intentional injury cases involving voluntary surrender in the total population. All regressions control for atmospheric conditions consisting of temperature, wind speed, precipitation, sunshine, and atmospheric pressure. The regressions are weighted using the total population (one million as the unit) of each city that year. *Benchmark* is the average of the dependent variable, and the *relative effect (%)* is the ratio of the estimated coefficient and *benchmark*. Standard errors in parentheses are robustly two-way clustered at the city and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.



Panel A



Panel B

Fig. 3. Lagged and cumulative effects of $PM_{2.5}$ on crime rates.

Notes. Panel A plots the relative contemporaneous and lagged effects, and Panel B visualizes the cumulative effects and the 95% confidence intervals over different time periods. In Panel A, each dot denotes the $\beta_\tau/benchmark$ estimated from eq. (4); for example, the second dot in each subfigure denotes the relative effect of yesterday's pollution, and so on for other dots. In Panel B, each dot denotes the sum of relative contemporaneous effects and the lagged effects estimated using eq. (4), which is $\sum_{\tau=0}^{k}\beta_\tau/benchmark$; for example, the second dot in each subfigure denotes the relative effect of today's and yesterday's pollution.

rate, but the magnitude of the increase is much smaller than that of the contemporaneous effect. Fig. 3 Panel B shows the cumulative effect on intentional injury persistently being positive from day 0 to day 7, which suggests that the effect of pollution on crime is not intertemporally shifting within a 7-day window, otherwise the cumulative effect should be zero. No significant cumulative effects within a 7-day window are found for other types of crime either. Given that the impact of pollution on crime is predominately contemporaneous rather than lagged, it is likely that the resultant pollution-induced crimes are impulsive, emotionally driven, and unpremeditated. This finding highlights the role of moods such as depression, anxiety, irritability, and hostility (Lu et al., 2020; Persico & Marcotte, 2022).

5.3. The role of pollution salience in shaping bad moods

The channels documented in the literature can be broadly summarized into two categories—physiological and psychological. Among the physiological factors, exposure to air pollution may increase blood pressure, hormones, insulin resistance, and biomarkers of oxidative stress and inflammation, which may in turn increase aggression (Li et al., 2017; Rammal et al., 2008). For the psychological factors, air pollution is documented to be correlated with stress, anxiety, impatience, and anti-social behavior (Chew et al., 2021; Lu et al., 2018, 2020; Power et al., 2015; Sass et al., 2017). Air pollution also affects mental health (Chen et al., 2023; Chen et al., 2024), and may even be linked to incidents of suicide (Molitor et al., 2023). We have to acknowledge that distinguishing cleanly between these two pathways using observational data is inherently challenging. In this subsection, we therefore introduce an additional perspective by exploring pollution salience as a complementary mechanism through which pollution affects criminal behavior.

We begin by examining whether higher $PM_{2.5}$ levels increase public attention to and concern about air pollution using online search behavior. Specifically, we collect the Baidu Index (BDI) for a set of widely used pollution-related keywords, including *AQI*, *$PM_{2.5}$*, *air pollution* ("空气污染" in Chinese), *air quality* ("空气质量" in Chinese), and *haze* ("霾" in Chinese). As shown in Table A.11 Panel A, higher ambient $PM_{2.5}$ concentration increases Baidu Index related to air pollution, indicating increased public attention to air pollution on polluted days. Moreover, using visibility distance as a proxy for perceived pollution salience, we find that reductions in visibility are accompanied by a pronounced rise in pollution-related search activity, as shown in Table A.11 Panel B.

Second, we estimate a horserace model that includes both $PM_{2.5}$ and ozone in the right-hand side of the regression equation. To address the endogeneity of ozone, we instrument local ozone with upwind zone from nearby cities. As shown in Table 8, both the OLS and 2SLS estimates show only visible $PM_{2.5}$, not invisible ozone, has a statistically significant effect on crime. As shown in Table A.12, the findings are robust when we flexibly control for weather conditions in a non-parametric manner, by adding bins of weather conditions, and utilize PPML estimator. This differs from the findings of Burkhardt et al. (2019), who report positive effects of both $PM_{2.5}$ and ozone on violent crime in the U.S. context. Two considerations are particularly relevant for reconciling the difference. Empirically, our specifications include a richer set of meteorological controls, such as sunshine duration and air pressure, which are correlated with ozone formation and have independent links to mood, and we use instrumental variables for both pollutants. Contextually, ozone plays a smaller role in shaping perceived air quality in China during our sample period: although average ozone concentrations are similar in China and the U.S., China's AQI is much more strongly driven by particulate pollution,[16] making public attention disproportionately focused on PM rather than ozone. More broadly, public awareness of air pollution in China rose sharply only after the 2013 haze episodes, and concern about ozone has remained far less salient than concern about PM.

The contrast between $PM_{2.5}$ and ozone is informative for the mechanism. Medical and biochemical literature have documented that ozone can directly impact brain chemistry by reducing the levels of serotonin, a neurotransmitter that functions as an inhibitor of aggression and impulsivity (González-Guevara et al., 2014; Murphy et al., 2013). More generally, both PM and ozone have been linked to physiological and neurological changes in a comparable manner, including blood pressure, stress hormone levels, inflammation, depression, and other biomarkers (see references summarized in Table A.13). If both pollutants can plausibly operate through similar physiological pathways, the fact that we observe effects for $PM_{2.5}$ but not ozone is consistent with a complementary role for pollution salience: visible high levels of PM can alter perceived pollution levels via salience, which can affect individuals' moods and in turn spawn criminal activities. We aim to clarify the mechanisms in Fig. 4. As stated by Gong et al. (2020), *actual* pollution alters individuals' behavior by affecting physiological and psychological factors (pathways ① and ②), but *perceived* pollution only affects individuals' behavior psychologically (pathway ①). In line with this distinction, experimental evidence suggests that merely observing high pollution can induce negative moods and make individuals more impatient and anti-social even without inhalation (Chew et al., 2021).

Third, we leverage the release of "Under the Dome" as an information shock that sharply raised public awareness of air pollution. Upon its release, the documentary attracted millions of clicks and views, and imposed a powerful shock on the public. The number of searches for keywords of "$PM_{2.5}$" or "haze" increased drastically within a month of the documentary's release (Tu et al., 2020). Before this documentary, the Chinese public did not have good knowledge of air pollution, especially PM. Motivated by this setting, we re-estimate our baseline specification using only the pre-release period. As shown in Table 9, $PM_{2.5}$ has no statistically significant effect on crime, which consolidates the statement that the pollution *salience* indeed plays an important role; otherwise, the effects should be present regardless of public's awareness of air pollution.

To further provide evidence on the salience mechanism, we construct a proxy for pollution salience based on **visibility anomaly.**

[16] EPA data show that in 2021 there are 2.5 times as many people in the U.S. living in counties with ozone concentrations above NAAQ levels than those with $PM_{2.5}$ concentrations above NAAQ levels (The U.S. EPA's Air Quality National Summary available at https://www.epa.gov/air-trends/air-quality-national-summary.). In contrast, the major pollutant in China is $PM_{2.5}$.

Table 8
The effect of $PM_{2.5}$ and O_3 on crime rates.

	(1)	(2)	(3)	(4)
	Dangerous Driving	Theft	Intentional Injury	Robbery
Panel A: OLS				
$PM_{2.5}$ (10 as the unit)	−0.0004	0.0005	0.0003**	−0.000003
	(0.0004)	(0.0004)	(0.0001)	(0.00004)
O_3 (10 as the unit)	0.0007	0.0002	0.0003	0.0001
	(0.0005)	(0.0007)	(0.0002)	(0.0001)
Relative effect of $PM_{2.5}$	−0.119	0.167	0.199	−0.014
Relative effect of O_3	0.216	0.058	0.183	0.535
Panel B: 2SLS				
$PM_{2.5}$ (10 as the unit)	−0.0004	0.0040	0.0023***	0.0001
	(0.0014)	(0.0032)	(0.0007)	(0.0003)
O_3 (10 as the unit)	−0.0010	0.0015	−0.0001	−0.0003
	(0.0015)	(0.0026)	(0.0007)	(0.0003)
Observations	454,985	454,985	454,985	454,985
Relative effect of $PM_{2.5}$	−0.127	1.316	1.604	0.519
Relative effect of O_3	−0.329	0.488	−0.052	−1.403
SW-F statistics of $PM_{2.5}$	238.497	238.497	238.497	238.497
SW-F statistics of O_3	549.124	549.124	549.124	549.124
Benchmark	0.304	0.305	0.145	0.019
KP-F statistics	118.016	118.016	118.016	118.016
Atmospheric conditions	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date

Notes. This table presents the OLS and 2SLS estimates of the impacts of $PM_{2.5}$ and O_3 on different crimes. $PM_{2.5}$ (O_3) is scaled by 1/10 and its coefficient represents the impacts of 10-unit $PM_{2.5}$ (O_3), respectively. The dependent variables are calculated using the number of corresponding crimes divided by the city's population that year. All regressions control for atmospheric conditions consisting of temperature, wind speed, precipitation, sunshine, and atmospheric pressure. The regressions are weighted using the total population (one million as the unit) of each city that year. *Benchmark* is the average of the dependent variable, and the *relative effect (%)* is the ratio of the estimated coefficient and *benchmark*. SW-F is the first-stage Sanderson-Windmeijer F-test. Standard errors in parentheses are robustly two-way clustered at the city and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The key idea is to isolate unexpected declines in visibility that are not mechanically driven by routine weather conditions or local seasonal patterns, but are instead more likely to reflect visually salient pollution episodes. Specifically, we residualize daily visibility distance with respect to contemporaneous meteorological conditions and city-by-month fixed effects by estimating

$$VisDist_{cmt} = \alpha + W'_{cmt}\theta + \mu_{cm} + \varepsilon_{cmt}, \tag{8}$$

where $VisDist_{cmt}$ denotes visibility distance in city c month m, and day t. The vector W_{cmt} includes average wind speed, temperature, precipitation, sunshine duration, and air pressure, and μ_{cm} denotes city-by-month fixed effects that absorb location-specific seasonality. We take the regression residual $\widehat{\varepsilon_{cmt}}$ as the visibility anomaly (*vis_resid*). By construction, more negative values of *vis_resid* indicate visibility that is *unexpectedly* low relative to what would be predicted by local seasonal patterns and weather conditions, which we interpret as days when air pollution is more visually salient to residents. We then divide the sample into terciles based on the distribution of visibility anomaly. Table 10 presents the pollution effects across different salience groups. We find that the pollution effect is concentrated entirely in the high-salience subsample, where visibility is anomalously low. In contrast, the estimated effects in the medium- and low-salience groups are small and statistically indistinguishable from zero. This pattern is consistent with the interpretation that the behavioral response to air pollution is amplified when pollution is more visually salient.

As a supplementary analysis, we further examine the interaction role of visibility and actual $PM_{2.5}$. If pollution salience amplifies the effect of air pollution on crime, the marginal impact of $PM_{2.5}$ should be stronger when visibility is low (when pollution salience is

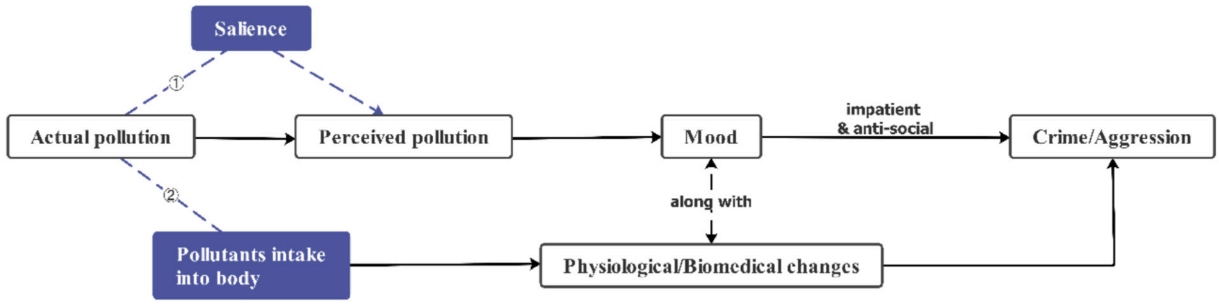


Fig. 4. Mechanism—the role of salience.
Notes. This figure illustrates the mechanisms through which air pollution affects crime.

Table 9
Effect of $PM_{2.5}$ on crime rates before the environmental documentary "Under the Dome".

	(1)	(2)	(3)	(4)	(5)
	$PM_{2.5}$	Dangerous Driving	Theft	Intentional Injury	Robbery
Panel A: OLS					
$PM_{2.5}$ (10 as the unit)		0.0007	−0.0001	0.0003	−0.0001
	/	(0.0006)	(0.0009)	(0.0002)	(0.0001)
Relative effect		0.246	−0.033	0.193	−0.331
Panel B: 2SLS					
1st stage					
Thermal Inversion	1.3645***				
	(0.1268)				
2nd stage					
$PM_{2.5}$ (10 as the unit)		−0.0017	0.0056	0.0009	0.0003
		(0.0023)	(0.0041)	(0.0011)	(0.0003)
Relative effect	/	−0.633	2.044	0.692	1.679
KP-F statistics		115.721	115.721	115.721	115.721
Benchmark		0.276	0.276	0.137	0.019
Observations	49,375	49,375	49,375	49,375	49,375
Atmospheric conditions	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date	City Date

Notes. This table presents the impacts of air pollution on different crimes before the documentary "Under the Dome" (spanning from 2014 to 28 Feb 2015). Panel A reports the OLS estimates of eqs. (1), and Panel B reports the 2SLS estimates of eqs. (2) and (3). Column (1) of Panel B presents the 1st stage results. $PM_{2.5}$ is scaled by 1/10 and its coefficient represents the impact of per 10-unit $PM_{2.5}$. The dependent variables from columns (2) to (5) are the crime rates of the corresponding crimes. All regressions control for atmospheric conditions consisting of temperature, wind speed, precipitation, sunshine, and atmospheric pressure. The regressions are weighted using the total population (one million as the unit) of each city that year. *Benchmark* is the average of the dependent variable, and the *relative effect (%)* is the ratio of the estimated coefficient and *benchmark*. Standard errors in parentheses are robustly two-way clustered at the city and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

high). To test this implication, we construct an indicator for days with visibility below the sample median and interact this indicator with $PM_{2.5}$ concentration. As shown in Table A.14, the estimated interaction term is positive and statistically significant, indicating that the effect of $PM_{2.5}$ on crime is indeed larger when visibility is relatively low. This pattern is consistent with a salience-based interpretation. At the same time, we emphasize that these results should be interpreted with caution, given the strong correlation between $PM_{2.5}$ and visibility. For this reason, we view the visibility-based analyses as supportive rather than cleanly identified evidence.

In summary, our discussion above complements rather than contradicts the existing literature documenting physiological and behavioral effects of air pollution. While previous studies emphasize biological responses or changes in time preferences, our analysis highlights the role of psychological factors—particularly mood—and the importance of pollution salience in shaping criminal

Table 10
$PM_{2.5}$ effects by pollution salience (proxied by visibility anomaly).

Dep. Var.	(1)	(2)	(3)
	Intentional Injury Crime Rate		
Visibility Anomaly	Tercile 1 (Highest Salience)	Tercile 2 (Medium Salience)	Tercile 3 (Lowest Salience)
Panel A: OLS			
$PM_{2.5}$ (10 as the unit)	0.0006*	0.0003	−0.0007
	(0.0003)	(0.0004)	(0.0006)
Panel B: 2SLS			
$PM_{2.5}$ (10 as the unit)	0.0043**	0.0027	0.0024
	(0.0020)	(0.0029)	(0.0026)
Observations	149,310	151,562	153,220
KP-F Stat.	221.339	266.711	364.196
Atmospheric conditions	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes
Cluster	City Date	City Date	City Date

Notes. This table reports estimates separately by terciles of the visibility anomaly distribution. *Visibility anomaly* is defined as the residual from regressing visibility distance on weather controls (wind speed, temperature, precipitation, sunshine, and air pressure), and city-by-month fixed effects. More negative residuals indicate unusually low visibility (higher salience). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

behavior. We do not rule out physiological channels, nor do we posit pollution salience or visibility as the *only* mechanism through which air pollution affects crime. Indeed, evidence from developed-country settings shows that pollution can affect crime even at relatively low and less visible pollution levels. In the context of China, where pollution is more severe and often visible salient to the naked eye, it gives us an opportunity to explore the mechanism of salience. We acknowledge the difficulty in determining whether physiological changes in the body or mood changes occur first, but we provide another psychological channel through which air pollution affects criminal behavior.

6. Conclusion

In this paper, we study how air pollution can affect the crime rate, utilizing the data from China Judgment Online. We find a 10 μg/m^3 rise in daily $PM_{2.5}$ leads to a significant 1.58% increase in the daily crime rate of intentional injury, while the increased $PM_{2.5}$ has no significant effect on crimes rates of dangerous driving, theft, and robbery. Additionally, marginalized and disadvantaged groups are more likely to be impacted by air pollution exposure to commit a crime. This paper also sheds light on the mood mechanism by which air pollution affects crime, by showing a greater effect on surrender intentional injury cases. Our findings highlight the role that pollution salience plays in influencing perceptions of pollution levels, which affect crime through moods.

Our findings provide support for the benefits of pollution control policies. Based on Chen & Liu (2013)'s calculation that the annual social cost of the crime of injury is 13.482–105.516 billion CNY in 2010, we carry out a back-of-the-envelope estimate of the additional annual cost of crime from 10 μg/m^3 $PM_{2.5}$ would be 0.2 billion to 1.67 billion CNY.

Our study also has important policy implications in the way that we identify vulnerable criminals as the individuals who are more likely to be repeat offenders, and who are likely to act alone, without the assistance of accomplices or weapons. These criminals may voluntarily surrender themselves afterwards. Therefore, policymakers can develop more targeted and effective crime prevention policies to reduce crime rates, particularly in areas with high levels of pollution.

Our findings on the role of pollution salience in the impact of pollution on crime also provide possible directions for policy development to reduce crime. The government or relevant authorities can reduce the likelihood of people experiencing negative emotions, or at least make people more aware of their mood, by circulating public service announcements or slogans that calm people down on polluted days, thus potentially reducing crimes caused by heightened emotions. In addition, these findings can guide urban design and the structuring of public spaces. Relevant authorities can design public spaces in pollution-prone areas to optimize visibility, reduce pollution's visual impact, and create aesthetically pleasing environments to counteract the negative psychological effects of pollution.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

Given her role as co-editor, Yu Qin had no involvement in the peer-review of this article and has no access to information regarding its peer-review. Full responsibility for the editorial process for this article was delegated to another journal editor. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Appendix

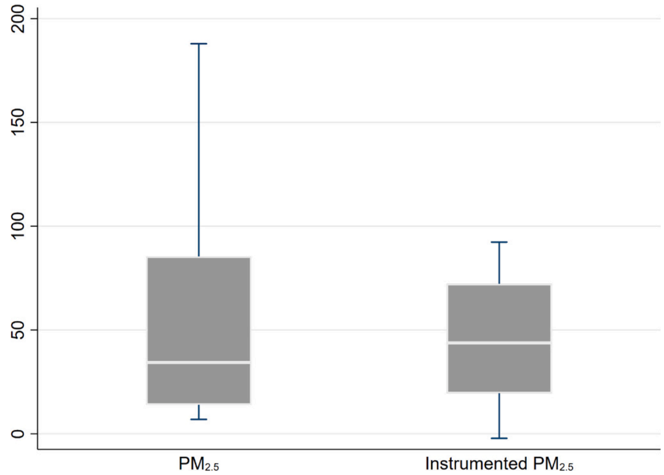

Fig. A.1. *Notes*. Box plots of raw and IV-fitted $PM_{2.5}$. The box lines represent the median, 10th, and 90th percentile, while the whiskers upper and lower limits are the 1st and 99th percentiles of the distribution.

Table A.1
Explanatory definitions of different criminal charges in the Criminal Law of the People's Republic of China.

Article 133.1 [Crime of Dangerous Driving (Article 133.1 of the Criminal Law)]
If a motor vehicle is driven on the road and falls under any of the following circumstances, the offender shall be sentenced to fixed-term imprisonment and shall also be fined: (1) Racing in violation of regulations with serious consequences; (2) Drunk driving a motor vehicle; (3) Engaging in school bus operations or passenger transportation, exceeding the rated passenger load or speed limit in a serious manner; (4) Transporting dangerous chemicals in violation of safety management regulations and endangering public safety.
Article 234 [Crime of Intentional Injury (Article 234 of the Criminal Law)]
Whoever intentionally inflicts bodily harm on another person shall be sentenced to fixed-term imprisonment, criminal detention or control of three years or less. Whoever commits the crime as prescribed in the preceding paragraph and causes severe injury to the victim shall be sentenced to fixed-term imprisonment of not less than three years but not more than ten years; whoever causes the victim's death or serious disability by means of especially cruel methods shall be sentenced to fixed-term imprisonment of not less than ten years, life imprisonment, or death penalty.
Article 263 [Crime of Robbery (Article 263 of the Criminal Law)]
Whoever commits robbery by means of violence, coercion, or other methods shall be sentenced to fixed-term imprisonment of not less than three years but not more than ten years and shall also be fined; whoever falls under any of the following circumstances shall be sentenced to fixed-term imprisonment of not less than ten years, life imprisonment, or death penalty, and shall also be fined or have their property confiscated: (1) Robbing by breaking into homes; (2) Robbing on public transportation; (3) Robbing banks or other financial institutions; (4) Multiple robberies or robberies involving a large amount of money; (5) Robbery causing severe injury or death; (6) Impersonating military or police personnel to commit robbery; (7) Robbery with firearms; (8) Robbery of military supplies or disaster relief, rescue, or aid materials.

(*continued on next page*)

Table A.1 (*continued*)

Article 264 [Crime of Theft (Article 264 of the Criminal Law)]

Whoever steals public or private property in relatively large amount, or commits theft repeatedly, burgles, carries deadly weapons while committing theft, or pickpockets shall be sentenced to fixed-term imprisonment, criminal detention, or control of three years or less, and may also be fined. Whoever commits theft under any of the following circumstances shall be sentenced to fixed-term imprisonment of not less than three years but not more than ten years, and shall also be fined:

(1) If the amount is large or there are other serious circumstances;

(2) If the amount is especially large or there are other especially serious circumstances, the offender shall be sentenced to fixed-term imprisonment of not less than ten years or life imprisonment, and may also be fined or have their property confiscated.

Table A.2

Summary of the estimated air pollution impacts on crime rates in the literature.

Paper	Country or region	Pollutant	Increase in pollutant concentration	Crime type	Increase in crime rates	Method (baseline)
This study	China	$PM_{2.5}$	10 $\mu g/m^3$	intentional injury (violent) theft, robbery, dangerous driving	1.58% insignificant	thermal inversion as IV
Burkhardt et al. (2019)	United States	$PM_{2.5}$ Ozone	10% (with a mean of 9.95 $\mu g/m^3$) 10%	violent crime	0.14% 0.30%	PPML
Herrnstadt et al. (2021)	Chicago	PM_{10}	1 s.d. (14.4 $\mu g/m^3$)	violent crime property crime	2.90% insignificant	wind direction as IV
Jones (2022)	8 States in the U.S.	dust storm days (+ 4.93 $\mu g/m^3$ $PM_{2.5}$)		violent crime - assault	12.70% 14.70%	dust storm as exogenous variable
Sarmiento (2023)	Mexico City New York	AQI	10-unit	hourly crime rate	0.33% 0.48%	wind direction as IV
Bondy et al. (2020)	London	AQI	10-unit	overall crime rate	2.60%	wind direction and thermal inversion as IV
Batkeyev and DeRemer (2023)	Almaty	$PM_{2.5}$	1% (with a mean of 89.71 $\mu g/m^3$)	total crime rate - violent crime - property crime	0.39% insignificant 0.39%	winds and temperature inversions as IV
Zarate Barrera, 2021	Mexico City	AQI	10-unit	crime rate	1.11%	winds as IV

Table A.3

Effects of air pollution on crime-related internet searches.

Dep. Var.	(1)	(2)	(3)	(4)	(5)
	Baidu Index For General Crime-Related Words				
	All	Criminal Activities	Maintaining Stability	Law and Order	Public security
Panel A: OLS					
$PM_{2.5}$	0.0009**	0.0002*	0.0004**	0.0001	0.0001
	(0.0004)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Relative effect	0.547	2.569	0.554	0.292	0.289
Panel B: 2SLS					
2nd stage					
$PM_{2.5}$	0.0041**	0.0021**	0.0012	0.0002	0.0007
	(0.0021)	(0.0009)	(0.0009)	(0.0010)	(0.0008)
Relative effect	2.592	21.895	1.613	0.447	1.772
KP-F Stat.	254.747	254.747	254.747	254.747	254.747
Observations	462,268	462,268	462,268	462,268	462,268
Benchmark	0.160	0.009	0.074	0.035	0.041
Atmospheric conditions	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date	City Date

Notes. The dependent variables are Baidu Index for different keywords including criminal activities ("犯罪活动" in Chinese), maintaining stability ("维稳" in Chinese), law and order ("治安" in Chinese), and public security ("公共安全" in Chinese), following Ma et al., 2025. All other specifications are the same as baseline. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4
Falsification test: the effect of $PM_{2.5}$ on indoor crime and outdoor crime.

	(1)	(2)
	Indoor	Outdoor
$PM_{2.5}$ (10 as the unit)	0.0038	0.0179*
	(0.0050)	(0.0107)
Observations	462,268	462,268
Relative effect	8.639	10.703
Benchmark	0.044	0.167
KP-F statistics	254.747	254.747
Atmospheric conditions	Yes	Yes
City-Year FE	Yes	Yes
City-Month FE	Yes	Yes
Year-Month FE	Yes	Yes
Day-of-Week FE (7)	Yes	Yes
Day-of-Month FE (31)	Yes	Yes
Holiday FE	Yes	Yes

Notes. This table presents 2SLS estimates of the impacts of $PM_{2.5}$ on indoor and outdoor crimes. $PM_{2.5}$ is scaled by 1/10 and its coefficient represents the impact of per 10-unit $PM_{2.5}$. The dependent variables are calculated using the number of corresponding crimes divided by the city's population that year. All regressions control for atmospheric conditions consisting of temperature, wind speed, precipitation, sunshine, and atmospheric pressure. The regressions are weighted using the total population (one million as the unit) of each city that year. *Benchmark* is the average of the dependent variable, and the *relative effect (%)* is the ratio of the estimated coefficient and *benchmark*. Standard errors in parentheses are robustly two-way clustered at the city and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5
City heterogeneity by other demographic and economic conditions.

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
	Intentional Injury Rate					
Group	Unemployment Rate		GDP Per Capita		Population	
	Low	High	Low	High	Low	High
$PM_{2.5}$ (10 as the unit)	0.0018*	0.0031***	0.0032***	0.0019**	0.0035**	0.0019**
	(0.0009)	(0.0010)	(0.0010)	(0.0010)	(0.0017)	(0.0008)
Coef. Diff.	−0.0013		0.0013*		0.0016*	
p-value	0.233		0.100		0.100	
Observations	186,080	192,531	198,797	200,633	201,262	203,931
Relative effect	1.280	2.035	2.746	1.147	2.154	1.454
Benchmark	0.141	0.151	0.117	0.169	0.162	0.128
KP-F Stat.	133.918	173.158	113.374	166.000	235.177	179.842
Atmospheric conditions	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date	City Date	City Date

Notes. This table examines city-level heterogeneity in the effect of air pollution on intentional injury rates across additional demographic and economic conditions. Cities are divided into high- and low-groups based on the median values of the unemployment rate, GDP per capita, and population, respectively. "Coef. Diff." reports the difference in the estimated $PM_{2.5}$ coefficient between the low and high groups within each dimension. Statistical significance of coefficient differences is assessed using Fisher's permutation tests, with *p*-values obtained via bootstrapping. All specifications remain the same as the baseline estimation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6
Offender heterogeneity of intentional injury (dummy as dependent variable, extensive margin).

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
	1(whether it is intentional injury with)					
	Age				Gender	
	<25	[25,35)	[35,45)	≥ 45	Female	Male
$PM_{2.5}$ (10 as the unit)	0.00005	0.0013*	0.0005	0.0003	0.0003	0.0027**
	(0.0005)	(0.0008)	(0.0007)	(0.0005)	(0.0004)	(0.0011)
Observations	462,268	462,268	462,268	462,268	462,268	462,268
Benchmark	0.045	0.104	0.082	0.024	0.025	0.263
KP-F Stat.	380.141	380.141	380.141	380.141	380.141	380.141
Atmospheric conditions	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date	City Date	City Date

Notes. The dependent variables are binary indicators for whether any crime of a given type occurred within a group (e.g., whether at least one intentional injury committed by a male offender occurs). All other specifications are the same as the baseline.

Table A.7
Robustness checks using different fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dangerous Driving	Theft	Intentional Injury	Robbery	Dangerous Driving	Theft	Intentional Injury	Robbery
Panel A: OLS								
$PM_{2.5}$ (10 as the unit)	−0.0008**	0.0008	0.0002*	−0.000001	0.00003	0.0007	0.0003**	−0.00001
	(0.0004)	(0.0005)	(0.0001)	(0.00005)	(0.0003)	(0.0004)	(0.0001)	(0.00005)
Relative effect	−0.275	0.276	0.165	−0.008	0.011	0.220	0.185	−0.050
Panel A: 2SLS								
$PM_{2.5}$ (10 as the unit)	−0.0019	0.0069	0.0024***	0.00003	−0.0001	0.0042	0.0023***	0.0001
	(0.0015)	(0.0045)	(0.0009)	(0.0003)	(0.0013)	(0.0032)	(0.0007)	(0.0003)
Relative effect	−0.634	2.285	1.660	0.135	−0.043	1.401	1.593	0.596
Observations	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268
Benchmark	0.303	0.303	0.144	0.019	0.303	0.303	0.144	0.019
Atmospheric conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes				
City-Month FE	Yes	Yes	Yes	Yes				
Year-Month FE	Yes	Yes	Yes	Yes				
Day-of-Year (365)	Yes	Yes	Yes	Yes				
City-Year-Month FE					Yes	Yes	Yes	Yes
Day-of-Week FE (7)					Yes	Yes	Yes	Yes
Day-of-Month FE (31)					Yes	Yes	Yes	Yes
Holiday FE					Yes	Yes	Yes	Yes

Notes. This table presents 2SLS estimates of the effects of $PM_{2.5}$ on different crimes estimated from alternative specifications using different fixed effects. $PM_{2.5}$ is scaled by 1/10 and its coefficient represents the impact of per 10-unit $PM_{2.5}$. The dependent variables are calculated using the number of corresponding cases divided by the city's population that year. All regressions control for atmospheric conditions consisting of temperature, wind speed, precipitation, sunshine, and atmospheric pressure. The regressions are weighted using the total population (one million as the unit) of each city that year. *Benchmark* is the average of the dependent variable, and the *relative effect (%)* is the ratio of the estimated coefficient and *benchmark*. Standard errors in parentheses are robustly two-way clustered at the city and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8
Effects of $PM_{2.5}$ on the number of crimes, using PPML.

	(1)	(2)	(3)	(4)
	Dangerous Driving	Theft	Intentional Injury	Robbery
$PM_{2.5}$ (10 as the unit)	−0.0020	0.0020**	0.0025**	0.0001
	(0.0014)	(0.0010)	(0.0010)	(0.0033)
Observations	458,652	467,419	464,489	400,865
Benchmark	1.191	1.286	0.572	0.090
Atmospheric conditions	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date

Notes. This table presents the impacts of air pollution on different crimes using PPML estimation. $PM_{2.5}$ is scaled by 1/10 and its coefficient represents the impact of per 10-unit $PM_{2.5}$. The dependent variables from columns (1) to (4) are the number of the corresponding crimes. All regressions control for atmospheric conditions consisting of temperature, wind speed, precipitation, sunshine, and atmospheric pressure. *Benchmark* is the average of the dependent variable. Standard errors in parentheses are robustly two-way clustered at the city and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9
Vulnerable criminals of other crimes.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Voluntary Surrender		First Offender		Accomplice		Weapon		Imprisonment		
	Y	N	Y	N	Y	N	Y	N	<1 yr	[1,5) yrs	≥ 5 yrs
Panel A: Dangerous driving											
$PM_{2.5}$ (10 as the unit)	−0.0000	−0.0004	−0.00002	−0.0004	−0.000001	−0.0004	0.00004	−0.0005	−0.0001	0.00003	0.00003
	(0.0003)	(0.0012)	(0.0004)	(0.0012)	(0.00002)	(0.0013)	(0.00003)	(0.0013)	(0.0013)	(0.0001)	(0.0001)
Relative effect	−0.003	−0.169	−0.056	−0.158	−0.908	−0.147	4.196	−0.161	−0.044	2.613	0.683
Panel B: Theft											
$PM_{2.5}$ (10 as the unit)	0.0010	0.0029	−0.0004	0.0043	−0.00004	0.0040	−0.0001	0.0040	0.0031	0.0005	0.0003**
	(0.0007)	(0.0026)	(0.0006)	(0.0029)	(0.0001)	(0.0031)	(0.0001)	(0.0031)	(0.0024)	(0.0008)	(0.0001)
Relative effect	2.242	1.138	−1.187	1.575	−1.921	1.323	−2.931	1.330	1.412	0.707	5.509
Panel C: Robbery											
$PM_{2.5}$ (10 as the unit)	−0.0001	0.0002	0.00001	0.0001	0.0001*	0.00002	−0.00001	0.0001	−0.00003	0.00004	0.0001
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.00005)	(0.0003)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Relative effect	−1.664	1.052	0.238	0.646	18.241	0.124	−0.458	0.688	−0.769	0.361	2.221
KP-F statistics	254.747	254.747	254.747	254.747	254.747	254.747	254.747	254.747	254.747	254.747	254.747
Observations	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268
Atmospheric conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table presents the heterogeneity in case characteristics for dangerous driving, theft, and robbery. $PM_{2.5}$ is scaled by 1/10 and its coefficient represents the impact of per 10-unit $PM_{2.5}$. The dependent variables are calculated using the number of corresponding cases (Y represents yes, N represents no) divided by the city's population that year; for example, *Voluntary Surrender (Y)* denotes the percentage of cases involving voluntary surrender in the total population. All regressions control for atmospheric conditions consisting of temperature, wind speed, precipitation, sunshine, and atmospheric pressure. The regressions are weighted using the total population (one million as the unit) of each city that year. *Benchmark* is the average of the dependent variable, and the *relative effect (%)* is the ratio of the estimated coefficient and *benchmark*. Standard errors in parentheses are robustly two-way clustered at the city and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10
Heterogeneity in criminal cases for intentional injury (dummy as dependent variable, extensive margin).

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	1(whether it is intentional injury with)										
	Voluntary Surrender		First Offender		Accomplice		Weapon		Imprisonment		
	Y	N	Y	N	Y	N	Y	N	<1 yr	[1,5) yrs	≥ 5 yrs
$PM_{2.5}$ (10 as the unit)	0.0024**	0.0030***	0.0010	0.0034***	−0.0001	0.0029**	0.0016*	0.0023*	0.0021**	0.0026***	0.0005
	(0.0010)	(0.0010)	(0.0008)	(0.0012)	(0.0001)	(0.0013)	(0.0009)	(0.0012)	(0.0011)	(0.0009)	(0.0004)
Observations	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268	462,268
Benchmark	0.168	0.200	0.086	0.263	0.001	0.311	0.138	0.230	0.216	0.136	0.018
KP-F Stat.	380.141	380.141	380.141	380.141	380.141	380.141	380.141	380.141	380.141	380.141	380.141
Atmospheric conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date	City Date	City Date	City Date	City Date	City Date	City Date	City Date

Notes. The dependent variables are binary indicators for whether any crime of a given type occurred within a group (e.g., whether at least one intentional injury committed by an armed offender occurs). All other specifications are the same as the baseline.

Table A.11
The impacts of $PM_{2.5}$ and visibility on online search activities related to air pollution.

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
	Baidu Index For					
	AQI	$PM_{2.5}$	Air Pollution	Air Quality	Haze	All
Panel A						
$PM_{2.5}$ (10 as the unit)	0.0356***	0.1602**	0.0132***	0.1037**	0.0306***	0.3436**
	(0.0112)	(0.0808)	(0.0032)	(0.0470)	(0.0062)	(0.1458)
Relative effect	15.116	19.267	10.939	22.520	19.115	18.839
KP-F Stat.	254.747	254.747	254.747	254.747	254.747	254.747
Observations	462,268	462,268	462,268	462,268	462,268	462,268
Benchmark	0.236	0.831	0.121	0.460	0.160	1.824
Panel B						
Visible distance (in 1 km)	−0.0542***	−0.2451**	−0.0199***	−0.1599**	−0.0477***	−0.5262**
	(0.0175)	(0.1243)	(0.0053)	(0.0726)	(0.0108)	(0.2256)
Relative effect	−23.022	−29.583	−16.568	−34.837	−29.926	−28.940
KP-F Stat.	64.641	64.641	64.641	64.641	64.640	64.641
Observations	459,924	459,924	459,924	459,924	459,924	459,924
Benchmark	0.236	0.828	0.120	0.459	0.160	1.818
Atmospheric conditions	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date	City Date	City Date

Notes. This table examines the impact of ambient air pollution (Panel A) and visibility (Panel B) on online search activity related to air pollution, estimated using 2SLS. The dependent variables are Baidu Index for different pollution-related keywords including *AQI*, *$PM_{2.5}$*, *air pollution*, *air quality*, *haze*, and the aggregate index ("All"), defined as the sum of the five individual indices. All other specifications are the same as baseline. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12
The effects of PM and ozone, alternative specifications.

	(1)	(2)	(3)	(4)
	Dangerous Driving	Theft	Intentional Injury	Robbery
Panel A: OLS (dependent variable: crime rates)				
$PM_{2.5}$ (10 as the unit)	−0.0007*	0.0003	0.0003**	0.000002
	(0.0004)	(0.0004)	(0.0001)	(0.00005)
O_3 (10 as the unit)	0.0001	0.000002	0.00003	0.00001
	(0.0001)	(0.0001)	(0.00002)	(0.000008)
Relative effect of $PM_{2.5}$	−0.224	0.101	0.224	0.010
Relative effect of O_3	0.018	0.001	0.020	0.054
Observations	454,985	454,985	454,985	454,985
Panel B: PPML (dependent variable: # of crimes)				
$PM_{2.5}$ (10 as the unit)	−0.0034**	0.0018*	0.0029***	0.0005
	(0.0014)	(0.0010)	(0.0010)	(0.0033)
O_3 (10 as the unit)	0.0002	−0.0002	0.0001	0.0004
	(0.0002)	(0.0001)	(0.0002)	(0.0004)
Benchmark	1.191	1.287	0.572	0.090
Observations	458,628	467,356	464,426	400,848
Panel C: 2SLS (dependent variable: crime rates)				
$PM_{2.5}$ (10 as the unit)	−0.0026**	0.0028	0.0022***	0.0001
	(0.0013)	(0.0030)	(0.0007)	(0.0003)
O_3 (10 as the unit)	−0.0001	0.0002	0.000008	−0.00002
	(0.0001)	(0.0003)	(0.0001)	(0.00003)
Relative effect of $PM_{2.5}$	−0.860	0.909	1.509	0.638
Relative effect of O_3	−0.019	0.059	0.006	−0.116
SW-F statistics of $PM_{2.5}$	232.330	232.330	232.330	232.330
SW-F statistics of O_3	606.337	606.337	606.337	606.337
Benchmark	0.304	0.305	0.145	0.019
KP-F statistics	115.075	115.075	115.075	115.075
Observations	454,985	454,985	454,985	454,985

(*continued on next page*)

Table A.12 (*continued*)

	(1) Dangerous Driving	(2) Theft	(3) Intentional Injury	(4) Robbery
Atmospheric conditions	bin	bin	bin	bin
City-Year FE	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date

Notes. This table presents the OLS, PPML, and 2SLS estimates of the impacts of $PM_{2.5}$ and O_3 on different crimes. $PM_{2.5}$ (O_3) is scaled by 1/10 and its coefficient represents the impacts of 10-unit $PM_{2.5}$ (O_3), respectively. The dependent variables in OLS and 2SLS estimation are calculated using the number of corresponding crimes divided by the city's population that year. The dependent variables in PPML are the number of the corresponding crimes. All regressions control for bins of atmospheric conditions, consisting of temperature, wind speed, precipitation, sunshine, and atmospheric pressure. The regressions are weighted using the total population (one million as the unit) of each city that year. *Benchmark* is the average of the dependent variable, and the *relative effect (%)* is the ratio of the estimated coefficient and *benchmark*. SW-F is the first-stage Sanderson-Windmeijer F-test. Standard errors in parentheses are robustly two-way clustered at the city and date level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13
Literature on biochemical reactions induced by ozone and $PM_{2.5}$.

	$PM_{2.5}$	Ozone
Blood pressure	(Fan et al., 2019; Oh et al., 2022; Soppa et al., 2017)	(Li, Dorans, et al., 2017; Panda et al., 2023; Rückerl et al., 2016)
Stress hormones	(Li, Cai, et al., 2017; Thomson, 2019)	(Murphy et al., 2013; Thomson, 2019)
Depressive symptoms	(Chu et al., 2019)	(Zhao, Markevych, Standl, Schulte-Körne, et al., 2019)
Oxidative stress and inflammation	(Li, Cai, et al., 2017; Panda et al., 2023; Rückerl et al., 2016)	(González-Guevara et al., 2014; Zhao, Markevych, Standl, Schikowski, et al., 2019)
Brain and nervous system	(L. Calderón-Garcidueñas et al., 2016; de Prado Bert, 2018; Thomson, 2019; Lilian Calderón-Garcidueñas et al., 2021; Costa et al., 2019)	(Cotter et al., 2023; Rivas-Arancibia et al., 2010)

Table A.14
The interactions between visibility and $PM_{2.5}$.

Dep. Var.	(1) Dangerous Driving	(2) Theft	(3) Intentional Injury	(4) Robbery
Panel A: OLS				
$PM_{2.5}$ (10 as the unit)	−0.0001	0.0007	0.0004***	−0.000008
	(0.0004)	(0.0004)	(0.0001)	(0.00005)
1(visible distance below median)	−0.0018	−0.0050	−0.0013	0.0004
	(0.0034)	(0.0039)	(0.0018)	(0.0007)
$PM_{2.5}$*1(visibility distance below median)	0.0001	0.0017**	0.0006*	−0.000002
	(0.0006)	(0.0007)	(0.0003)	(0.0001)
Panel B: 2SLS				
2nd stage				
$PM_{2.5}$ (10 as the unit)	−0.0010	0.0040	0.0026***	0.0001
	(0.0016)	(0.0036)	(0.0008)	(0.0003)
1(visible distance below median)	0.0014	−0.0178	−0.0100***	0.00003
	(0.0071)	(0.0144)	(0.0036)	(0.0014)
$PM_{2.5}$*1(visibility distance below median)	−0.0004	0.0036*	0.0019***	0.00005
	(0.0011)	(0.0021)	(0.0006)	(0.0002)
KP-F Stat.	199.232	199.232	199.232	199.232
Benchmark	0.303	0.304	0.144	0.019
Observations	454,101	454,101	454,101	454,101
Atmospheric conditions	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Day-of-Week FE (7)	Yes	Yes	Yes	Yes
Day-of-Month FE (31)	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
Cluster	City Date	City Date	City Date	City Date

Notes. This table examines the interaction between air pollution and pollution salience, proxied by visibility. The dependent variables are daily crime rates for dangerous driving, theft, intentional injury, and robbery. $PM_{2.5}$ is measured in units of 10 $\mu g/m^3$. 1(visible distance below median) is an indicator equal to one if daily visibility distance is below the sample median, and zero otherwise. The interaction term captures whether the effect of air pollution on crime is stronger on low-visibility (high-salience) days. Panel A reports OLS estimates, while Panel B reports 2SLS estimates, where $PM_{2.5}$ is instrumented by thermal inversion. All specifications are the same as the baseline. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Data availability

Data will be made available on request.

References

Ahl, B., Cai, L., & Xi, C. (2019). Opportunities, challenges, and issues. *The China Review, 19*(2), 1–14.

Aragón, F. M., Miranda, J. J., & Oliva, P. (2017). Particulate matter and labor supply: The role of caregiving and non-Linearities. *Journal of Environmental Economics and Management, 86*(November), 295–309.

Arceo, E., Hanna, R., & Oliva, P. (2016). Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from mexico City. *The Econometrics Journal, 126*(591), 257–280.

Barwick, P. J., Li, S., Lin, L., & Zou, E. (2019). *"From fog to smog: The value of pollution information." (Working Paper Series)*.

Barwick, P. J., Li, S., Rao, D., & Zahur, N. B. (2024). The healthcare cost of air pollution: Evidence from the worlds largest payment network. *The Review of Economics and Statistics*. https://doi.org/10.1162/rest_a_01430

Batkeyev, B., & DeRemer, D. R. (2023). Mountains of evidence: The effects of abnormal air pollution on crime. *Journal of Economic Behavior and Organization, 210* (June), 288–319.

Baysan, C., Burke, M., González, F., Hsiang, S., & Miguel, E. (2019). Non-economic factors in violence: Evidence from organized crime, suicides and climate in mexico. *Journal of Economic Behavior and Organization, 168*(December), 434–452.

Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy, 76*(2), 169–217.

Behrer, A. P., & Bolotnyy, V. (2022). Heat, crime, and punishment. In *Policy Research Working Paper Series, January*. https://ideas.repec.org//p/wbk/wbrwps/9909.html.

Bondy, M., Roth, S., & Sager, L. (2020). Crime is in the air: The contemporaneous relationship between air pollution and crime. *Journal of the Association of Environmental and Resource Economists, 7*(3), 555–585.

Burkhardt, J., Bayham, J., Wilson, A., Carter, E., Berman, J. D., O'Dell, K., … Pierce, J. R. (2019). The effect of pollution on crime: Evidence from data on particulate matter and ozone. *Journal of Environmental Economics and Management, 98*(November), Article 102267.

Calderón-Garcidueñas, L., Leray, E., Heydarpour, P., Torres-Jardón, R., & Reis, J. (2016). Air pollution, a rising environmental risk factor for cognition, neuroinflammation and neurodegeneration: The clinical impact on children and beyond. *Revista de Neurologia, 172*(1), 69–80.

Calderón-Garcidueñas, L., Stommel, E. W., Rajkumar, R. P., Mukherjee, P. S., & Ayala, A. (2021). Particulate air pollution and risk of neuropsychiatric outcomes. What we breathe, swallow, and put on our skin matters. *International Journal of Environmental Research and Public Health, 18*(21). https://doi.org/10.3390/ijerph182111568

Cameron, L., Meng, X., & Zhang, D. (2019). Chinas sex ratio and crime: Behavioural change or financial necessity? *The Econometrics Journal, 129*(618), 790–820.

Chen, F., Zhang, X., & Chen, Z. (2023). Air pollution and mental health: Evidence from China health and nutrition survey. *Journal of Asian Economics, 86*(June), Article 101611.

Chen, L., Liu, Z., & Tang, Y. (2022). Judicial transparency as judicial centralization: Mass publicity of court decisions in China. *Journal of Contemporary China, 31*(137), 726–739.

Chen, S., & Liu, F. (2013). Estimating the social cost of crimes during the transition period in China. *World Economic Papers, 3*, 42–64.

Chen, S., Oliva, P., & Zhang, P. (2022). The effect of air pollution on migration: Evidence from China. *Journal of Development Economics, 156*, Article 102833.

Chen, S., Oliva, P., & Zhang, P. (2024). Air pollution and mental health: Evidence from China. *AEA Papers and Proceedings. American Economic Association, 114*(May), 423–428.

Chen, S., & Li, T. (2020). The effect of air pollution on criminal activities: Evidence from the NOx budget trading program. *Regional Science and Urban Economics, 83* (July), Article 103528.

Chew, S. H., Huang, W., & Li, X. (2021). Does haze cloud decision making? A natural laboratory experiment. *Journal of Economic Behavior and Organization, 182*, 132–161.

Chu, C., Zhang, H., Cui, S., Han, B., Zhou, L., Zhang, N., Su, X., et al. (2019). Ambient PM2.5 caused depressive-like responses through Nrf2/NLRP3 signaling pathway modulating inflammation. *Journal of Hazardous Materials, 369*, 180–190.

Correia, S., Guimarães, P., & Zylkin, T. (2020). Fast poisson estimation with high-dimensional fixed effects. *The Stata Journal, 20*(1), 95–115.

Costa, L. G., Cole, T. B., Dao, K., Chang, Y.-C., & Garrick, J. M. (2019). Developmental impact of air pollution on brain function. *Neurochemistry International, 131* (December), Article 104580.

Cotter, D. L., Campbell, C. E., Sukumaran, K., McConnell, R., Berhane, K., Schwartz, J., … Herting, M. M. (2023). Effects of ambient fine particulates, nitrogen dioxide, and ozone on maturation of functional brain networks across early adolescence. *Environment International, 177*(July), Article 108001.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature, 52*(3), 740–798.

Dickson, M. F., Wasarhaley, N. E., & Matthew Webster, J. (2013). A comparison of first time and repeat rural DUI offenders. *Journal of Offender Rehabilitation, 52*(6), 421–437.

Doleac, J. L., & Sanders, N. J. (2015). Under the cover of darkness: How ambient light influences criminal activity. *The Review of Economics and Statistics, 97*(5), 1093–1103.

Dong, R., Fisman, R., Wang, Y., & Xu, N. (2021). Air pollution, affect, and forecasting bias: Evidence from Chinese financial analysts. *Journal of Financial Economics, 139*(3), 971–984.

Du, X. (2023). Symptom or culprit? Social media, air pollution, and violence. *SSRN Working Paper.*. https://doi.org/10.2139/ssrn.4380957

Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of Political Economy, 81*(3), 521–565.

Fan, F., Wang, S., Zhang, Y., Dandan, X., Jia, J., Li, J., … Huo, Y. (2019). Acute effects of high-level PM2.5 exposure on central blood pressure. *Hypertension, 74*(6), 1349–1356.

Fu, S., Viard, V. B., & Zhang, P. (2021). Air pollution and manufacturing firm productivity: Nationwide estimates for China. *The Econometrics Journal, 131*(640), 3241–3273.

Gong, S., Lu, J. G., Schaubroeck, J. M., Li, Q., Zhou, Q., & Qian, X. (2020). Polluted psyche: Is the effect of air pollution on unethical behavior more physiological or psychological? *Psychological Science, 31*(8), 1040–1047.

González-Guevara, E., Martínez-Lazcano, J. C., Custodio, V., Hernández-Cerón, M., Rubio, C., & Paz, C. (2014). Exposure to ozone induces a systemic inflammatory response: Possible source of the neurological alterations induced by this gas. *Inhalation Toxicology, 26*(8), 485–491.

Herrnstadt, E., Heyes, A., Muehlegger, E., & Saberian, S. (2021). Air pollution and criminal activity: Microgeographic evidence from Chicago. *American Economic Journal: Applied Economics, 13*(4), 70–100.

Jacob, B., Lefgren, L., & Moretti, E. (2007). The dynamics of criminal behavior: Evidence from weather shocks. *The Journal of Human Resources, 42*(3), 489–527.

Jones, B. A. (2022). Dust storms and violent crime. *Journal of Environmental Economics and Management, 111*, Article 102590.

Kearney, M. S., & Levine, P. B. (2015). Media influences on social outcomes: The impact of MTVs 16 and pregnant on teen childbearing. *The American Economic Review, 105*(12), 3597–3632.

Li, H., Cai, J., Chen, R., Zhao, Z., Ying, Z., Wang, L., Chen, J., et al. (2017). Particulate matter exposure and stress hormone levels. *Circulation, 136*(7), 618–627.

Li, W., Dorans, K. S., Wilker, E. H., Rice, M. B., Ljungman, P. L., Schwartz, J. D., Coull, B. A., et al. (2017). Short-term exposure to ambient air pollution and biomarkers of systemic inflammation: The Framingham heart study. *Arteriosclerosis, Thrombosis, and Vascular Biology, 37*(9), 1793–1800.

Liebman, B. L., Roberts, M. E., Stern, R. E., & Wang, A. Z. (2020). Mass digitization of chinese court decisions: How to use text as data in the field of chinese law. *Journal of Law and Courts, 8*(2), 177–201.

Lin, S., & Xu, B. (2024). Quantitative characteristics, sentencing rules, and governance paths of sexual assault crimes against left behind children: An empirical analysis based on judicial documents. *Juvenile Delinquency Prevention Research, 13*, 4–10.

Liu, Z., Wong, T. J., Yi, Y., & Zhang, T. (2022). Authoritarian transparency: Chinas missing cases in court disclosure. *Journal of Comparative Economics, 50*(1), 221–239.

Lu, J. G., Lee, J. J., Gino, F., & Galinsky, A. D. (2018). Polluted morality: Air pollution predicts criminal activity and unethical behavior. *Psychological Science, 29*(3), 340–355.

Lu, J. G., Lee, J. J., Gino, F., & Galinsky, A. D. (2020). Air pollution, state anxiety, and unethical behavior: A Meta-analytic review. *Psychological Science, 31*(6), 748–755.

Ma, H., Pan, Y., & Xu, M. (2025). The criminogenic consequence of export slowdown: Evidence from millions of court judgement documents in China. *The Economic Journal, 135*(671), 2242–2275.

Ma, H., Xu, M., You, W., & Feng, J. (2026). Assessing the impact of surveillance cameras on crime. *Journal of Development Economics, 178*, Article 103557.

Madestam, A., Shoag, D., Veuger, S., & Yanagizawa-Drott, D. (2013). Do political protests matter? Evidence from the tea party movement. *Quarterly Journal of Economics, 128*(4), 1633–1685.

Molitor, D., Mullins, J. T., & White, C. (2023). Air pollution and suicide in rural and urban America: Evidence from wildfire smoke. *Proceedings of the National Academy of Sciences, 120*(38), Article e2221621120.

Murphy, S. R., Schelegle, E. S., Miller, L. A., Hyde, D. M., & Van Winkle, L. S. (2013). Ozone exposure alters serotonin and serotonin receptor expression in the developing lung. *Toxicological sciences: an official journal of the Society of Toxicology, 134*(1), 168–179.

Oh, E., Choi, K.-H., Kim, S. R., Kwon, H.-J., & Bae, S. (2022). Association of indoor and outdoor short-term PM2.5 exposure with blood pressure among school children. *Indoor Air, 32*(3), Article e13013.

Panda, S. R., Chaudhari, V. B., Ahmed, S., Kwatra, M., Jala, A., Ponneganti, S., … Naidu, V. G. M. (2023). Ambient particulate matter (PM2.5) exposure contributes to neurodegeneration through the microbiome-gut-brain axis: Therapeutic role of melatonin. *Environmental Toxicology and Pharmacology, 101*(August), Article 104183.

Persico, C., & Marcotte, D. E. (2022). Air quality and suicide. In *Working Paper Series. National Bureau of Economic Research*. https://doi.org/10.3386/w30626

Power, M. C., Kioumourtzoglou, M.-A., Hart, J. E., Okereke, O. I., Laden, F., & Weisskopf, M. G. (2015). The relation between past exposure to fine particulate air pollution and prevalent anxiety: Observational cohort study. *BMJ (Clinical research ed.), 350*(March), Article h1111.

de Prado Bert, P., Henderson Mercader, E. M., Pujol, J., Sunyer, J., & Mortamais, M. (2018). The effects of air pollution on the brain: A review of studies interfacing environmental epidemiology and neuroimaging. *Current Environmental Health Reports, 5*(3), 351–364.

Rammal, H., Bouayed, J., Younos, C., & Soulimani, R. (2008). Evidence that oxidative stress is linked to anxiety-related behaviour in mice. *Brain, Behavior, and Immunity, 22*(8), 1156–1159.

Ranson, M. (2014). Crime, weather, and climate change. *Journal of Environmental Economics and Management, 67*(3), 274–302.

Rivas-Arancibia, S., Guevara-Guzmán, R., López-Vidal, Y., Rodríguez-Martínez, E., Zanardo-Gomes, M., Angoa-Pérez, M., & Raisman-Vozari, R. (2010). Oxidative stress caused by ozone exposure induces loss of brain repair in the hippocampus of adult rats. *Toxicological sciences: an official journal of the Society of Toxicology, 113*(1), 187–197.

Rückerl, R., Schneider, A., Hampel, R., Breitner, S., Cyrys, J., Kraus, U., … Peters, A. (2016). Association of novel metrics of particulate matter with vascular markers of inflammation and coagulation in susceptible populations -results from a panel study. *Environmental Research, 150*(October), 337–347.

Sarmiento, L. (2023). The nonlinear effects of air pollution on criminal behavior: Evidence from mexico City and New York. *Environmental Research: Health, 1*(2), Article 021001.

Sass, V., Kravitz-Wirtz, N., Karceski, S. M., Hajat, A., Crowder, K., & Takeuchi, D. (2017). The effects of air pollution on individual psychological distress. *Health & Place, 48*(November), 72–79.

Singh, T. P., & Visaria, S. (2021). Up in the air: Air pollution and crime – Evidence from India. *SocArXiv*. https://doi.org/10.31219/osf.io/hs4xj

Soppa, V. J., Schins, R. P. F., Hennig, F., Nieuwenhuijsen, M. J., Hellack, B., Quass, U., Kaminski, H., et al. (2017). Arterial blood pressure responses to short-term exposure to fine and ultrafine particles from indoor sources - A randomized sham-controlled exposure study of healthy volunteers. *Environmental Research, 158*(October), 225–232.

Tealde, E. (2022). The unequal impact of natural light on crime. *Journal of Population Economics, 35*(3), 893–934.

Thomson, E. M. (2019). Air pollution, stress, and allostatic load: Linking systemic and central nervous system impacts. *Journal of Alzheimer's Disease: JAD, 69*(3), 597–614.

Tu, M., Zhang, B., Xu, J., & Lu, F. (2020). Mass media, information and demand for environmental quality: Evidence from the 'Under the Dome. *Journal of Development Economics, 143*, Article 102402.

Zarate Barrera, T. (2021). Too polluted to sin: Dirty skies, crime and adaptation responses in Mexico City. *SSRN Working Paper.*. https://doi.org/10.2139/ssrn.4271924

Zhao, T., Markevych, I., Standl, M., Schikowski, T., Berdel, D., Koletzko, S., … Heinrich, J. (2019). Short-term exposure to ambient ozone and inflammatory biomarkers in cross-sectional studies of children and adolescents: Results of the GINIplus and LISA birth cohorts. *Environmental Pollution, 255*(Pt 2), Article 113264.

Zhao, T., Markevych, I., Standl, M., Schulte-Körne, G., Schikowski, T., Berdel, D., Koletzko, S., et al. (2019). Ambient ozone exposure and depressive symptoms in adolescents: Results of the GINIplus and LISA birth cohorts. *Environmental Research, 170*(March), 73–81.