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Does air pollution cause more car accidents? Evidence from auto insurance claims

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ABSTRACT

Using a proprietary data set of auto insurance claims from May 2014 to December 2016, this paper examines the influence of air pollution on the number and severity of traffic accidents in China. Combining an instrumental variable strategy with high-dimensional fixed effects, we find that air pollution significantly increases the occurrence of traffic accidents, with each 1 μg/m^3 increase in the particulate matter 2.5 (PM2.5) resulting in a 0.12 % increase in traffic accident probability and a 0.40 % increase in traffic accident number within one day. A different pattern is revealed in our analysis of accident severity, evidenced by a decrease of 1.20 % in the average claim ratio compared to its mean value and a reduction of 26 yuan in the average claim amount made with an increase of 1 μg/m^3 in PM2.5. Combining the effect on the number and severity of traffic accidents, for each 1 μg/m^3 increase in daily PM2.5, the district daily claim amount decreases by approximately 34 yuan. Further analysis indicates that this may be related to cautious driving behavior resulting from the driver's increased risk aversion. By exercising caution and care on the road, drivers can reduce the negative influence of air pollution on road safety and avoid non-subjective behavioral biases.

1. Introduction

Air pollution and its adverse effects on health, attention span, behavior, and cognitive functioning have received extensive attention in the last few years (Currie & Neidell, 2005; Currie & Walker, 2019; Guarnieri & Balmes, 2014; Knittel, Miller, & Sanders, 2016; Landrigan et al., 2018; Suglia, Gryparis, Wright, Schwartz, & Wright, 2008). There has been increasing discussion of how changes in air pollution affect individuals' purchase of housing (Qin, Wu, & Yan, 2019), masks and air purifiers (Ito & Zhang, 2020), and insurance (Chang, Huang, & Wang, 2018), as well as the impact of air pollution on stock investments (Li, Luo, & Soderstrom, 2017), labor supply and productivity (Chang, Graff Zivin, Gross, & Neidell, 2016; Graff Zivin & Neidell, 2012; Hanna & Oliva, 2015), and criminal activity and unethical behavior (Bondy, Roth, & Sager, 2020; Herrnstadt, Heyes, Muehlegger, & Saberian, 2021; Lu, Lee, Gino, & Galinsky, 2018). Air pollution can reduce traffic accidents by increasing drivers' risk aversion or increase accidents by impairing cognition or irritating respiratory organs (Sager, 2019; Shr, Hsu, Hwang, & Jung, 2023). To elucidate the effects of air pollution on road safety, we investigate the concurrent impact of air pollution on traffic accident numbers and the severity of these accidents.

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To examine the impact of air pollution on road safety, we use a unique proprietary data set comprising auto insurance claims from a Chinese auto insurance provider, including 262,625 claim records with detailed insured and claim information from May 2014 to the end of 2016. The data set includes the timestamp and location of each claim, which allows us to assign each accident to the corresponding district and day of occurrence and, subsequently, match it with the corresponding air quality data. In addition, the data include basic demographic information on those insured, such as their age, gender, and information on their insurance contracts. This enables us to test potential mechanisms of air pollution effects by examining heterogeneity.

To overcome potential endogeneity issues affecting the relationship between traffic accidents and air pollution, we use two instrumental variable (IV) strategies, which use changes in atmospheric temperature inversion and upwind pollution based on wind direction and wind speed as exogenous shocks to local pollution levels. Atmospheric temperature inversion acts as lids over cities, trapping pollutants and worsening air quality, but they are not directly affected by traffic. In previous studies, it has been used as an instrument for particulate matter 2.5 (PM2.5) to estimate the effects of PM2.5 on a variety of outcomes, including health (Arceo, Hanna, & Oliva, 2016), road safety (Sager, 2019), crime (Bondy et al., 2020), and flight delay (Chen, Chen, Xie, Mueller, & Davis, 2023). Recent studies have also shown that upwind pollution based on wind direction and wind speed induces an exogenous shock to local air pollution and can be used as a supplementary IV for air pollution (Chen, Chen, Lei, & Tan-Soo, 2021; Heyes & Zhu, 2019). In addition, we control for a series of fixed effects of time-invariant characteristics and time trends to help us avoid potential endogeneity problems. To further eliminate their influence, we include control variables capturing environmental and weather factors (such as temperature, dew point temperature, wind speed, precipitation, visibility, and three weather dummy variables for fog, rain, and snow).

We find that every 1 μg/m^3 increase in the PM2.5 leads to a 0.12 % increase in the probability of claims and a 0.40 % increase in the number of claims within one day in China. The estimated effect is economically important considering the large number of accidents on China's roads yearly.[1] We further explore the effect of air pollution on accident severity, as represented by the average claim ratio and the average claim amount for each accident. We find a significant negative effect of air pollution on accident severity, which indicates that accidents with higher levels of air pollution are less severe. Our preferred specification estimates that an increase of 1 μg/m^3 in average PM2.5 concentration leads to a 1.20 % decrease in the average claim ratio compared to its mean value and a 26.23 yuan decrease in the average claim amount. Taking into account this combined effect on the number of claims and their average claim amount, we estimate that a district's claim amount decreases by approximately 33.54 yuan for each 1 μg/m^3 increase in daily PM2.5. Therefore, although air pollution does appear to cause an increase in traffic accidents, people are becoming more cautious, which reduces the severity of the accidents. It is possible that on polluted days, the increase in traffic accidents is not caused deliberately by drivers, and that people are more cautious and take precautions to avoid these non-subjective behavioral biases.[2]

To ensure the robustness of our findings, we perform several additional tests. We first use the air quality index (AQI) as an alternative specification for air quality. We find that our results hold. Secondly, we control for the fourth-degree polynomial of ground temperature to take into account the possibility of a more complex relationship between temperature and traffic accidents, and the results remain consistent. To address our concern about drivers' unfamiliarity with road conditions outside of town, we examine a local sample of accidents only occurring in the local area and repeat our analysis. Fourth, we consider a subsample of areas with low precipitation, e.g., less than 0.5 mm, in order to reduce the effect of rain or snow on driving behavior and accidents. Our main regression results continue to hold. To alleviate concerns about spurious contemporaneous effects caused by lagged pollution, we include the PM2.5 concentrations from the three previous days in the model as additional controls and obtain similar results. Additionally, we use supplemental IVs to assess the impact of air pollution on traffic accidents. It strengthens our confidence in our results that we obtain similar estimates across all IV empirical approaches. We also employ alternative functional forms, an alternative measure for the number of claims, and a random PM2.5 indicator to assess the robustness of the analyses. The results of all these analyses are consistent.

We test the effect of unexpected and persistent air pollution on traffic accidents. We find that unexpected air pollution can lead to more accidents and lower average claim ratio and claim amount after drivers develop expectations about future pollution levels. Specifically, we observe a 0.09 % increase in the probability of accidents and a 0.32 % increase in the number of accidents for every 1 μg/m^3 increase in unexpected PM2.5. We can also find a more significant decrease in both the average claim ratio (0.01 %) and average claim amount (0.68 %) accordingly. A possible explanation is that when people encounter unexpectedly high pollution, they become more cautious or protective while driving than usual, thus mitigating part of the increase in the probability and number of accidents caused by air pollution, resulting in a more substantial decrease in the severity of accidents. To examine whether the effect of air pollution on accidents becomes more pronounced when there has been an extended period of air pollution, we include an indicator for persistent pollution and its interaction terms with air pollution variables as additional regressors in the baseline regression. We find that persistent pollution does not have a significant impact on accidents.

Next, we explore the heterogeneity of the results. We find that air pollution causes more accidents during warm months with lower severity. We also observe significant differences across demographic groups, especially among the elderly, for whom the effects of air

[1] In 2016, there were 212,846 traffic accidents in China, including 145,820 automobile accidents, according to the China Statistical Yearbook. Our estimates suggest that a 1 μg/m^3 increase in PM2.5 per day leads to 583 car accidents, which translates into a monetary value of 2.26 million yuan.

[2] Non-intentional actions that lead to a non-optimal result are termed non-subjective behavior biases. We found that air pollution increases the number of accidents, but making drivers more cautious reduces the severity of accidents. The increase in the number of accidents is primarily due to drivers' judgment being passively impaired by air pollution instead of intentional behavior. Accordingly, pollution-induced behavioral bias is a non-subjective behavioral bias.

pollution are more pronounced than for younger age groups, resulting in more significant increases in accidents and larger reductions in claims for the elderly group than for the other two groups.

To illuminate the mechanism through which air pollution negatively affects the average claim ratio and average claim amount, we examine the relationship between air pollution and the risk preferences of the driver. We use the amount of commercial auto insurance coverage, the premium of compulsory auto liability insurance, and drivers' claim history to reflect the driver's risk preferences. Our evidence suggests that air pollution leads to a lower average claim ratio and claim amounts for more risk-averse drivers compared with less risk-averse drivers. Studies find that air pollution is strongly related to conservative behavior (Chang et al., 2018; Zhang & Mu, 2018). Poor air quality makes drivers more cautious, resulting in less serious accidents. The effect is even more pronounced when drivers are risk-averse. Thus, a rise in traffic accidents caused by air pollution may not necessarily result from drivers' subjective decisions. Furthermore, there is no evidence that drivers' avoidance behaviors reduce the severity of accidents.

Our paper directly contributes to the vast literature on the consequences of air pollution by quantifying the effects of air pollution on road safety. In particular, our paper is most related to recent works studying air pollution and traffic accidents. Sager (2019) finds that air pollution can significantly increase the number of vehicles involved in traffic accidents, while Shr et al. (2023) report the opposite results. However, relying only on data on the number of road traffic accidents means that the analysis ignores how air pollution affects the severity of traffic accidents. In contrast with Sager (2019) and Shr et al. (2023), we use auto insurance claims data, taking the number of claims as a proxy for the number of traffic accidents and the average claim ratio and average claim amount as proxies for the severity of accidents, respectively, to extend the analysis of the economic consequences of air pollution on road safety. We expand the focus of the research from the single impact of air pollution on the number of accidents to the effect on the severity of accidents and provide some evidence of the effect of air pollution on driving behavior.

Second, we provide direct evidence showing that air pollution can discourage risky behaviors, in addition to the literature that shows it reduces such behaviors associated with financial investment. Air pollution can damage cognitive abilities and result in bad mood states (Badman & Jaffe, 1996; Block & Calderón-Garcidueñas, 2009; Szyszkowicz, 2007; Yang, Tsai, & Huang, 2011). Both cognitive level and mood are negatively correlated with the degree of risk aversion (Chou, Lee, & Ho, 2007; Dohmen, Falk, Huffman, & Sunde, 2018; Yuen & Lee, 2003). Discussions of the impact of air pollution on risk appetite mainly take a financial investment perspective (e.g., Heyes, Neidell, & Saberian, 2016; Levy & Yagil, 2012) and argue that air pollution negatively affects the total return of stocks. This relationship is caused by collective changes in risk aversion, which air pollution affects through changes in mood or cognitive function. However, the conclusion that air pollution changes risk appetite and is ultimately reflected in investment performance cannot be directly transferred to how air pollution affects nonfinancial decisions. Shr et al. (2023) propose that air quality could reduce traffic accidents by increasing drivers' risk aversion through visual channels, but they do not provide direct evidence of drivers' risk preferences. By measuring individual risk appetite, we provide new direct evidence that when air pollution occurs, the reduction of risky behavior occurs not only in relation to financial investment but also in relation to nonfinancial decisions.

Our paper provides evidence for the positive role of self-control in defending against the adverse effects of air pollution. Self-control can be defined as the capacity to override, delay, interrupt, or alter dominant response tendencies, and to regulate behavior, thoughts, and emotions (Bandura, 1989; Carver & Scheier, 1981, 1982; Metcalfe & Mischel, 1999; Rothbaum, Weisz, & Snyder, 1982; Vohs & Baumeister, 2004), and it is related to a wide range of behaviors, such as reduced aggression and criminality (DeWall, Baumeister, Stillman, & Gailliot, 2007; Gottfredson & Hirschi, 1990; Pratt & Cullen, 2000), fewer financial and impulse control problems (Baumeister, 2002; Baumeister & Vohs, 2004; Strömbäck, Lind, Skagerlund, Västfjäll, & Tinghög, 2017), and a low appetite for risk-taking (Baron, 2003; Borghans, Golsteyn, Heckman, & Meijers, 2009; Wood, Pfefferbaum, & Arneklev, 1993). We propose that self-control can reduce the severity of traffic accidents. Air pollution induces aggressive behavior and reduces road safety (Bondy et al., 2020; Sager, 2019). Self-control, which inhibits an individual's impulsive and aggressive behavior (Baron, 2003; DeWall et al., 2007), is associated with a reduction in risky driving behavior (De Ridder, Lensvelt-Mulders, Finkenauer, Stok, & Baumeister, 2012). Drivers exert more self-control when air quality is poor, mitigating the negative impact of air pollution on road safety and reducing the severity of accidents.

The remainder of the paper is organized as follows. Section 2 describes the data used. Section 3 introduces the empirical strategy, including the construction of the IVs. Section 4 presents the estimation results. Section 5 discusses the risk preference and avoidance behavior mechanisms through which air pollution affects the insurance claim ratio and claim amount. Finally, Section 6 concludes the paper.

2. Data sources

2.1. Auto insurance claims data

We use a unique proprietary data set obtained from an auto insurance company in China, which comprises all insurance contracts signed by its branches in Beijing, Shanghai, Inner Mongolia Autonomous Region, Shandong, and Sichuan provinces, as well as corresponding insurance claim data. The insurance claims dataset contains detailed information about each claim record, including the exact accident time, location (the address where the accident occurred), claim amount, and details about the vehicles and drivers involved. Moreover, the contract dataset provides information on premiums, insurance types, contract terms, vehicle types, and information regarding the insured, such as age and gender, which we exploit for further analyses. While the claims data covers 31 provinces and municipalities in China (excluding Hong Kong, Macao, and Taiwan), we focus on the claims within the five provinces above from May 2014 to December 2016 since car owners generally purchase insurance where they drive the most. Fig. 1 illustrates the spatial distribution of traffic accidents by plotting the total number of claims across districts in the five provinces over the sample period.

In order to demonstrate the representativeness of our sample, we compare it with public data from three different perspectives. First, the sample insurance company does not particularly appeal to risk-averse or risk-taking drivers. We calculate the average premium per policy and claim frequency for compulsory auto liability insurance in our sample and compare them to other renowned insurance companies, as shown in Fig. A.1.[3] Results indicate that the average premium per policy and the claim frequency among drivers in our sample fall within reasonable ranges and do not show significant deviations. This indicates that the risk preferences of drivers in our sample are not significantly different from those of the general driver population.

Second, our sample's spatiotemporal distribution of accidents is consistent with that of officially published data. We compare our sample and the Shanghai Road Risk Map (2017 Edition), published by the Shanghai Bureau of the China Insurance Regulatory Commission (now known as the Shanghai Regulatory Bureau of the China Banking and Insurance Regulatory Commission).[4] Based on compulsory auto liability insurance claims in Shanghai for 2016, this authoritative report provides comprehensive insights into the spatiotemporal distribution of accidents.[5] We plot the time distribution of traffic accidents using the 2016 Shanghai subsample from our data, as shown in Fig. A.2. The time distribution of accidents in this subsample is in keeping with the overall time distribution of accidents in Shanghai, as shown in the Road Risk Map. Additionally, the time distributions by gender and age in our subsample also exhibit similar trends to those observed in the Road Risk Map sample, as shown in Fig. A.3.[6] Moreover, the Road Risk Map indicates that traffic accidents in Shanghai are concentrated in the central urban areas, a pattern which is also evident in our sample data. This similarity in the spatiotemporal distribution of traffic accidents supports the representativeness of our sample, at least for Shanghai in 2016.

Thirdly, the average demographics of drivers in our dataset are comparable to the national average. The sample used in this paper consisted of 262,625 claim records, with a mean age of 37.82 years for insured individuals. Most insured individuals (77.35 %) are between the ages of 26 and 50 (including both 26 and 50). There are 72.02 % males in the sample and 27.98 % females, which is similar to the 72.77 % male share reported by the Ministry of Public Security (MPS) of the People's Republic of China in 2016. Moreover, the MPS's first report on driver age distribution in 2018 indicated that drivers aged 26–50 accounted for 72.70 %, slightly less than the 77.35 % observed in our insurance claims data. Considering the varying growth rates across age groups, particularly the increasing number of elderly drivers, this difference is within reasonable bounds. According to this comparison, our sample is in good alignment with national demographics in terms of gender and age distribution, especially for the population segment most commonly involved in insurance claims.[7]

2.2. Air pollution data

Air pollution data are obtained from the China National Environmental Monitoring Center of the Ministry of Ecology and Environment (MEE) of the People's Republic of China. The MEE provides real-time data from its monitoring stations. It had 946 stations in 2014 when its operations commenced; these increased over the study period, with approximately 1500 monitoring stations in 2015 and 2016. The measures of pollutants include the AQI and multiple individual air quality indexes that measure sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), carbon monoxide (CO), particulate matter 10 (PM10), and PM2.5. We focus on the PM2.5 and the AQI measurement, as people are more likely to be aware of and respond to these measures; specifically, we use PM2.5 for the main

[3] The renowned companies include PICC Property and Casualty Company (PICC), Ping An Property Insurance Company (Ping An), China Pacific Property Insurance Company (CPIC), China Life Property & Casualty Insurance Company (CLIC), China Continent Property & Casualty Insurance Company (CCIC), China United Property Insurance Company (United), Sunshine Property and Casualty Insurance Company (Sunshine), and China Taiping Insurance Holdings Company (Taiping). The average premium per policy and the claim frequency of these companies are obtained from publicly available actuarial reports on their compulsory auto liability coverage. To ensure comparability, the data for calculations is based on 303,569 claims over the years 2014–2016. The sample used in other parts of this paper covers May 2014 to December 2016.

[4] Available at https://www.shanghai.gov.cn/nw31406/20200820/0001-31406_1285150.html; https://mp.weixin.qq.com/s/jv6V8Ha2ROEH4aPPKWmoLA.

[5] The statistical criteria used in our sample for traffic accidents differ significantly from those used in commonly available official data sources, such as the statistical yearbooks published by the National Bureau of Statistics, local statistical bureaus, or traffic accident reports published by traffic management authorities. For example, before 2018, the Shanghai Statistical Yearbook included only accidents handled through standard procedures. Since 2018, it has expanded to include accidents processed through simplified procedures. For more details, see https://tjj.sh.gov.cn/tjnj/nj19.htm?d1=2019tjnj/C2406.htm. In contrast, our sample encompasses all accidents for which insurance claims were filed, including those handled through standard procedures, those resolved via simplified procedures, and those settled by mutual agreement between the parties involved, regardless of the specific handling procedures.

[6] In the Shanghai Road Risk Map, we observe an inconsistency between the overall sample and the gender sub-samples regarding accident time distributions. Specifically, during the first peak period (8 a.m.), both males and females experience higher accident rates than the overall sample. There may be discrepancies in the calculation methods between the overall sample and the subsample. We, therefore, concentrate primarily on comparing trends rather than exact values when analyzing the time distribution for gender and age-specific samples.

[7] In addition, we examine the weekly distribution of traffic accidents and analyze vehicle characteristics in our sample. We then compare these findings with data reported in the news, which supports our data validity. These analyses are not included in the main text to maintain brevity but are available upon request.

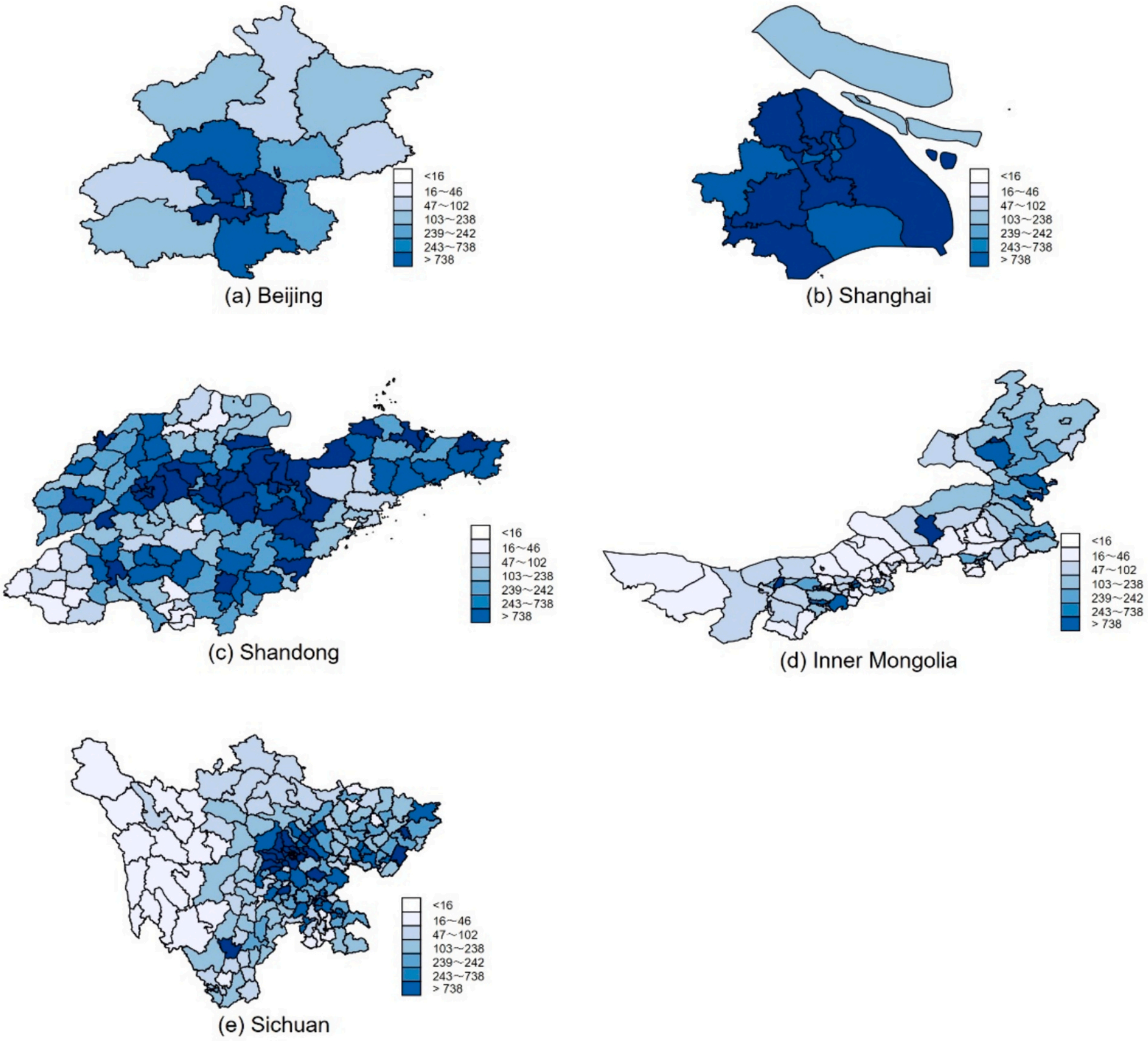

Fig. 1. Geographical distribution of claims.
This figure shows the geographical distribution of claims in Beijing, Shanghai, Shandong, Inner Mongolia, and Sichuan from May 2014 to December 2016.

analysis and AQI for the robustness test.[8]

The Technical Regulation on Ambient Air Quality Index published by the MEE in 2012 classifies air quality according to six levels: excellent, good, lightly polluted, moderately polluted, heavily polluted, and severely polluted. The cutoff points are 50, 100, 150, 200, and 300, respectively—thus, the higher the AQI, the worse the pollution and the effects on health. As the AQI comprises six pollutants, PM2.5 data cannot be directly compared with AQI data by levels (Qin et al., 2019). Therefore, following the cutoffs of PM2.5 from the MEE's Technical Regulation on Ambient Air Quality (2012) designed to alleviate concerns over the comparison with the AQI, we create dummy variables for the cutoff points of PM2.5 at 35, 75, 115, 150, 250, and 350 ($\mu g/m^3$), resulting in seven dummy variables (including the omitted category) that represent the pollution levels.[9]

Figure 2 depicts the distribution of the daily average PM2.5 in Beijing, Shanghai, Shandong, Sichuan, and the Inner Mongolia Autonomous Region between 2014 and 2016. There are 894 days of data for each region, with variations in pollution levels by city or

[8] AQI is a composite index of multiple pollutants, calculated based on the predominant pollutant in the air on a given day. However, specific pollutant indicators are more comparable than AQI, as the predominant pollutant can vary daily. Thus, we use PM2.5 for the main analysis.

[9] See Table 1 of the Technical Regulation on Ambient Air Quality Index available at https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/jcffbz/201203/t20120302_224166.shtml.

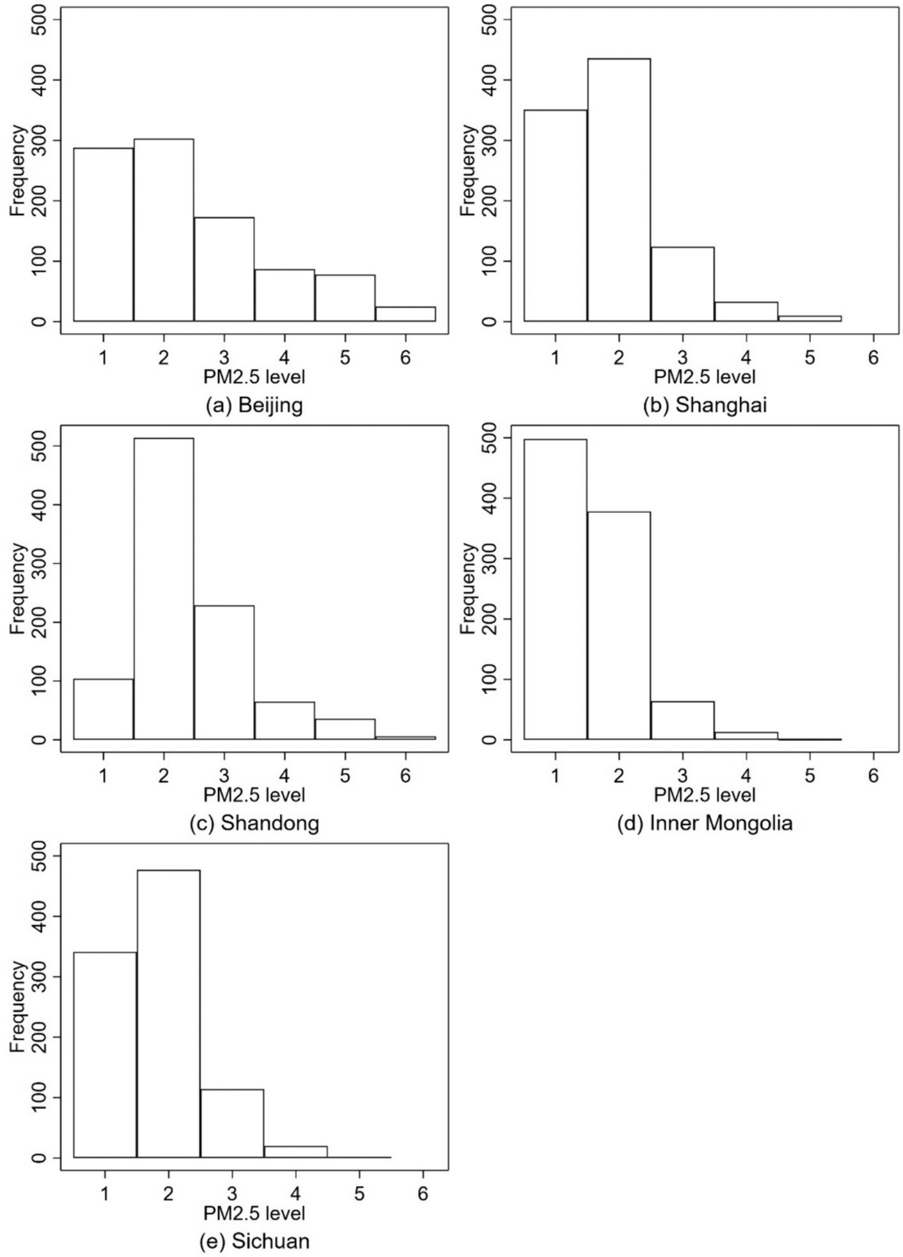

Fig. 2. Air quality (2014.5.13–2016.12.31).
This figure shows the distribution of daily air quality indexes in Beijing, Shanghai, Shandong, Inner Mongolia, and Sichuan from May 2014 to December 2016. During the sample period, a total of 4770 PM2.5 day-province observations and 158 PM2.5 day-province observations are defined as "heavily polluted" (involving PM2.5 values greater than 150) in these five provinces.

province. The number of healthy days (PM2.5 values below 75) accounts for most of the data.

2.3. Environment and atmospheric temperature data

We obtain our weather data from the National Oceanic and Atmospheric Administration's (NOAA) Global Surface Summary of the Day (GSOD). The data provide daily summary weather conditions from 1279 observation stations, including temperature (Fahrenheit), dew point temperature (Fahrenheit), wind speed (knots), precipitation (inches), visibility (miles), as well as three weather dummy variables for fog, rain, and snow as control variables. The dew point is mainly used as a proxy for humidity since humidity is unavailable in the NOAA weather data set (Zhang & Mu, 2018).

To solve the potential endogeneity problem that air quality is affected by traffic flow, we use atmospheric temperature inversion as an IV obtained from the MERRA-2 (Modern-Era Retrospective analysis for Research and Applications version 2) released by the National Aeronautics and Space Administration (NASA). This data is provided with a spatial resolution of 0.5 × 0.625 degrees (approximately 45 km × 55 km) and reports the air temperature for each of 42 sea-level pressure layers every six hours. The atmospheric temperature inversion data is constructed by averaging the temperature across grid points within each district for each day and layer. In addition, we calculate the upwind pollution IV based on wind direction and wind speed from NOAA's Integrated Global Radiosonde Archive (IGRA).

2.4. Merged final sample and summary statistics

Our analysis focuses on 451 districts within Beijing, Shanghai, Inner Mongolia Autonomous Region, Shandong, and Sichuan provinces. We geocode each claim record using the AutoNavi map API, resulting in 346,323 observations including zero counts, and 82,897 observations excluding zero counts. The key indicators we defined are the claim status, number of claims, average claim ratio, and average claim amount. Specifically, the claim status is defined using a dummy variable that indicates whether an accident occurred within a district on a given day (1 for accidents, 0 for non-accidents). The number of claims is defined as the daily count of claims within each district (exclusive of zero claims). The average claim ratio refers to the daily average ratio of claim amount to insurance coverage per accident within each district.[10] Within each district, the average claim amount is defined as the daily average claim amount.[11]

Then, we employ the inverse-distance weighting (IDW) method to match air pollution data and weather conditions from stations to districts. The IDW method is widely used in the literature for imputed pollution or weather data (Chen et al., 2021; Currie & Neidell, 2005). The basic algorithm takes the weighted average of all monitoring stations within the circle with a certain radius for the centroid of each district. Following Chen et al. (2023), we use a radius of 50 km, and our results are robust to a variety of radius distances. Each district's PM2.5 and AQI readings are aggregated into a daily level using the average of the hourly readings.

Summary information about daily claim status, the number of claims, the average claim ratio, the average claim amount, air quality, and environmental conditions for each district are presented in Table 1. We winsorize the variables at the 1 % and 99 % levels to mitigate the influence of extreme values. Our analysis focuses on two samples: the extensive margin (all days) and the intensive margin (days with accidents). With an average claim status of 0.27, less than 27 % of districts experienced car accidents on average each day. The average PM2.5 and AQI values (57.05 μg/m^3 and 86.52, respectively) suggest generally good air quality according to China's national standards.[12] By examining only accident days in the intensive margin sample, we observe the mean of claim numbers, average claim ratio, and claim amount are 3.10 times, 0.80 %, and 3869.97 yuan, respectively. We can find a higher average pollution level (PM2.5: 60.60 μg/m^3, AQI: 90.33) compared to the extensive margin sample. This is likely because accident days tend to coincide with periods of higher air pollution, which highlights the potential link between traffic accidents and air quality.

3. Empirical strategy

3.1. The fixed-effects model

We first introduce a fixed-effects model for estimating the contemporary effects of air pollution on the number of claims and claim amounts. The primary econometric framework is as follows:

$$Y_{i,t} = Constant + \beta PM2.5_{i,t} + \lambda_1 Weather_{i,t} + \lambda_2 Holiday_t + District_i \times Year_t \times Week_t + DOW_t + \epsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ represents the outcome of interest, in district i on day t. For our main specification, $Y_{i,t}$ represents the dummy variable of whether an accident occurred, the logarithm of the number of traffic accidents, the average claim ratio, or the logarithm of the average claim amount. $PM2.5_{i,t}$ measures the daily average air pollution in district i on day t, which is a continuous variable. $Weather_{i,t}$ controls for weather around district i on day t, including air temperature, dew point temperature, wind speed, visibility, precipitation, and three weather dummy variables for fog, rain, and snow to control the potential effect of the environmental factors. $Holiday_t$ is the dummy variable for national statutory holidays. In the full specification, we also control for the year-by-week-by-district and day-of-the-week fixed effects. We adopt two-way robust standard errors at the district-day level.

In addition to using the continuous measurement of the PM2.5, in the following specification, we adopt a categorical measure of the PM2.5 using the four levels (at the corresponding cutoff points: 35, 75, and 115, as explained in Section 2.2) to allow for the possible

[10] To calculate the average claim ratio at the district-day level, we follow the following procedure: We first calculate the claim ratio for each individual accident by dividing the claim amount by the insurance coverage. Next, we aggregate the claim ratios for all accidents occurring within the same district on the same day. Finally, we calculate the average claim ratio by dividing this aggregated claim ratio by the number of accidents that occurred in that district on that particular day.

[11] The average claim amount at the district-day level is calculated by the following steps: First, we aggregate the claim amounts for all accidents that occurred within the same district on the same day. We then calculate the average claim amount by dividing the aggregated claim amount by the number of accidents that occurred in that district on that particular day.

[12] According to the Technical Regulation on Ambient Air Quality Index issued by the MEE, an AQI below 100 or PM2.5 levels below 75 μg/m^3 indicate good air quality.

Table 1
Summary statistics.

Variable	N	mean	sd	min	max
Panel A: Extensive margin sample					
claim status	346,323	0.267	0.443	0.000	1.000
PM25 ($\mu g/m^3$)	346,323	57.053	41.642	0.000	582.512
AQI	346,323	86.517	49.205	0.000	487.663
temperature (Fahrenheit)	346,323	58.283	18.090	3.163	87.191
dew point temperature (Fahrenheit)	346,323	45.499	20.855	−11.800	76.836
visibility (miles)	346,323	8.518	5.162	1.080	18.600
wind speed (knots)	346,323	4.600	2.204	1.271	12.963
precipitation (inches)	346,323	0.086	0.220	0.000	1.330
fog	346,323	0.101	0.302	0.000	1.000
rain	346,323	0.261	0.439	0.000	1.000
snow	346,323	0.016	0.124	0.000	1.000
Panel B: Intensive margin sample					
number of claims	82,897	3.092	3.401	1.000	19.000
average claim ratio (%)	82,897	0.801	1.787	0.046	14.485
average claim amount (yuan)	82,897	3869.974	7876.005	300.000	60,858.000
PM25 ($\mu g/m^3$)	82,897	60.603	41.605	0.224	524.573
AQI	82,897	90.326	49.366	9.222	483.942
temperature (Fahrenheit)	82,897	59.394	17.753	3.163	87.191
dew point temperature (Fahrenheit)	82,897	47.362	20.189	−11.800	76.836
visibility (miles)	82,897	7.389	4.706	1.080	18.600
wind speed (knots)	82,897	4.664	2.306	1.271	12.963
precipitation (inches)	82,897	0.076	0.206	0.000	1.330
fog	82,897	0.089	0.285	0.000	1.000
rain	82,897	0.284	0.451	0.000	1.000
snow	82,897	0.014	0.119	0.000	1.000

This table shows the descriptive statistical analysis of our sample from May 2014 to December 2016. Panels A and B report the summary statistics for the extensive and intensive samples, respectively. *Claim status* is a dummy variable indicating whether an accident occurred within a district on a given day (1 for accident, 0 otherwise). *number of claims* is defined as the daily count of claims within each district (excluding zero counts). *claim ratio* is defined as the daily average ratio of claim amount to insurance coverage per accident within each district. *Claim amount* is defined as the daily average claim amount within each district. *PM2.5* and *AQI* are the concentration of air pollution. *Fog*, *snow*, and *rain* are dummy variables of the different types of weather.

nonlinear effect of air pollution:

$$Y_{i,t} = Constant + \sum_{n=2}^{4} \beta_n PM2.5_{n,i,t} + \lambda_1 Weather_{i,t} + \lambda_2 Holiday_t + District_i \times Year_t \times Week_t + DOW_t + \epsilon_{i,t} \tag{2}$$

where $PM2.5_{n,i,t}$ denotes dummy variables for different levels of the daily average PM2.5 around district i on day t, and the excellent air quality group is used as the omitted category. Here, we combine the moderate and more severe pollution levels because there are relatively few days at these levels. This approach ensures that we have sufficient observations in each category to prevent the results from being confounded by the sample size. The rest of the notations are the same as in Eq. (1).

Figure 3 illustrates the relationships between air pollution and four outcome variables, by excluding the meteorological factors and the full set of fixed effects. As the figure shows, the probability and number of claims are positively related to the daily PM2.5 level, while the average claim ratio and claim amount are negatively correlated with the PM2.5 concentration.

3.2. The instrumental variable approach

Air pollution at various locations may not be random because human activities are directly related to air pollution. For instance, traffic volume may simultaneously influence accident numbers and pollution levels (Green, Heywood, & Navarro, 2016; Sager, 2019). Additionally, accidents that result in fires may also increase pollution concentrations. Therefore, the endogeneity of pollution levels may lead to biased estimates when a simple regression analysis is performed with OLS estimators. The OLS results are insufficient to determine the relationship between air pollution and the probability, number, average claim ratio, and average claim amount of accidents. Therefore, in addition to the baseline OLS regression of eq. (1) and the categorical measure of the independent variable specification of eq. (2), we employ an IV approach to alleviate potential endogeneity issues. Specifically, we use atmospheric temperature inversion and upwind pollution based on wind direction and wind speed as IVs. Since the atmospheric temperature inversion, wind speed, and wind direction depend on meteorological and geographical factors, we can be confident that the IVs are valid and exogenous.

Generally, the temperature changes inversely with altitude, and the temperature inversion is a meteorological phenomenon that

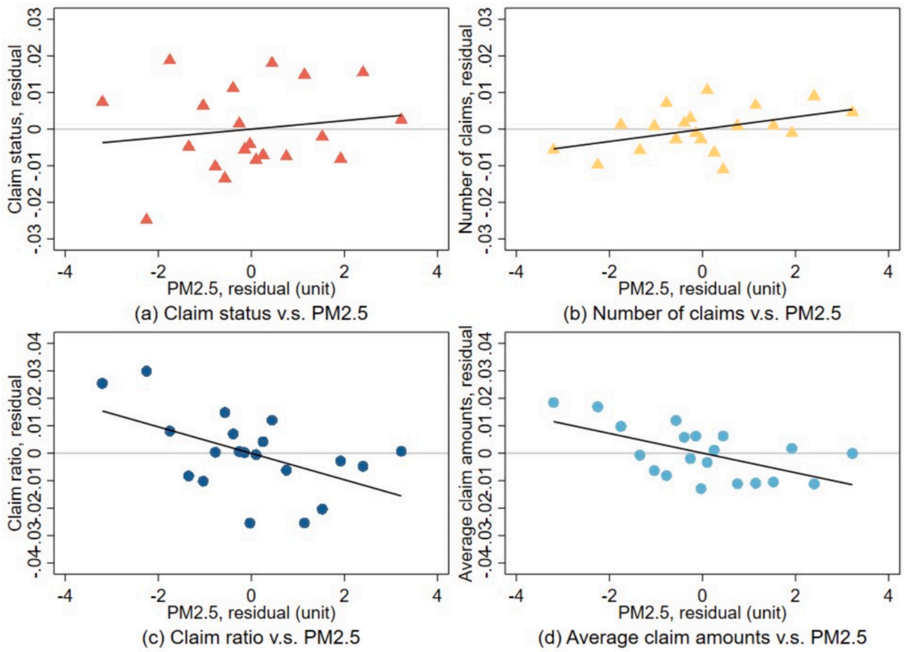

Fig. 3. Residual outcome variables against residual PM2.5 Levels.
This figure plots the residual claim status against residual PM2.5 levels in Panel (a), the residual number of claims against residual PM2.5 levels in Panel (b), the residual average claim ratio against residual PM2.5 levels in Panel (c), and the residual average claim amount against residual PM2.5 levels in Panel (d). Each dot represents an average district date within a bin. We first regress the outcome variables and PM2.5 levels on the meteorological factors and the set of fixed effects in the main specification. Then, we use the residuals to plot these patterns in binned scatters.

occurs when air temperature abnormally increases with altitude. During inversion episodes, warm air at higher altitudes prevents pollutants from rising and dispersing, trapping pollutants under the inversion, and allowing the pollutants to accumulate. We use the sea-level pressure information to represent different layers and corresponding temperature readings to construct atmospheric temperature inversion variables.[13] Following Chen, Oliva, and Zhang (2018) and Sager (2019), we calculate a continuous temperature difference between the first (lowest) layer and the second (lowest). Unlike Chen, Oliva, and Zhang (2018) and Sager (2019), we do not use fixed-height sea-level pressure layers due to the substantial variation in elevation across regions. An area like the Inner Mongolia Autonomous Region, which averages an altitude of 1000 m, differs significantly from a low-lying area like Shanghai, which is only 4 m above sea level. To account for these differences, we use the difference in temperature between the two sea-level pressure layers closest to the ground. This approach provides greater accuracy and broader applicability compared to methods relying on fixed heights. Moreover, we use continuous differences rather than dummy variables for atmospheric temperature inversion because it may provide an improved representation of vertical ventilation conditions (He, Liu, & Salvo, 2019; Sager, 2019). In the first stage of the two-stage least squares (2SLS) regression, we incorporate the continuous difference of the atmospheric temperature inversion into the regression equation. We propose the following 2SLS model:

1st stage:

$$P_{i,t} = Constant + \delta Z_{i,t} + \gamma_1 Weather_{i,t} + \gamma_2 Holiday_t + District_i \times Year_t \times Week_t + DOW_t + \epsilon_{i,j,t} \tag{3}$$

2nd stage:

$$Y_{i,t} = Constant + \beta \widehat{P}_{i,t} + \lambda_1 Weather_{i,t} + \lambda_2 Holiday_t + District_i \times Year_t \times Week_t + DOW_t + \epsilon_{i,t} \tag{4}$$

where $P_{i,t}$ is the average daily concentration of PM2.5 or other pollutants measuring the air pollution in district i on day t. $Z_{i,t}$ is the measure of atmospheric temperature inversion strength in district i on day t. The rest of the notations are the same as in Eq. (1).

Air pollutants can also be significantly affected by wind speed and direction (Shr et al., 2023; Wang et al., 2017). This is particularly true in Chinese cities, where wind patterns heavily influence pollutant movement across regions (Fu, Viard, & Zhang, 2021). Therefore, we construct another IV for air pollution based on wind speed and direction data. Specifically, following Chen et al. (2021) and Heyes and Zhu (2019), the equation for constructing the upwind pollution IV (UP_{it}) for district i on day t is written as:

[13] Atmospheric temperature inversion is calculated by subtracting the temperature of the higher layer from the temperature of the layer one level below. The lower the pressure, the higher the height.

$$UP_{i,t} = \sum_{n \neq i} \frac{Pl_{n,t} \times WS_{n,t}}{D^2_{n,i}} \times max\{cos(\gamma_{n,i} - \beta_{n,t}), 0\} \tag{5}$$

where district n is the nearby district within a 100–300 km radius[14] of the district i. $Pl_{n,t}$ is the air pollution in the nearby district n on day t. $WS_{n,t}$ is the wind speed in district n on day t. $D^2_{n,i}$ is the squared distance between each district n and district i. The amount of contribution from district n is determined by taking the cosine of the difference between the angle of the north direction of district n and the straight line to district i ($\gamma_{n,i}$) and the angle of the north direction of the district n and wind direction ($\beta_{n,t}$). It is possible for the angular difference to be less than zero, thus we bound the cosine decomposition in eq. (5) to be nonnegative since downwind cities will not contribute to upwind city air pollution. On other things being equal, pollution imports from district n by wind to district i are greater when: (a) the districts are close, (b) wind speed is high on the day, and (c) the angle between the wind direction and an imaginary line connecting the two districts is narrow. Wind patterns cause highly localized changes in air quality (Bondy et al., 2020). Nonetheless, given that drivers move across space, pollution levels in the district where the accident occurred may not adequately reflect the driver's exposure prior to the accident. Therefore, we employ atmospheric temperature inversion IV in the baseline specification and upwind pollution IV as a robustness test.

4. Results

4.1. Baseline results

Table 2 shows the effect of air pollution on the claim status in column (1), the number of accidents in column (2), and the severity of accidents in columns (3) and (4) in each district during a day. In all the reported regressions, we control for year-by-week-by-district and day-of-the-week fixed effects, weather conditions, and dummy variables for national statutory holidays. We adopt two-way clustered standard errors at the district-day level.

Panel A of Table 2 shows the results of OLS estimation in Eq. (1), and panel B shows 2SLS estimations in Eq. (3) and Eq. (4).[15] The smallest value of the Kleibergen-Paap F-tests is greater than 10, suggesting that the weak IV problem does not exist. Since a potential endogeneity problem biases the OLS estimates toward zero (Chen et al., 2021), the absolute value of the 2SLS coefficients is greater than the OLS coefficients.

There is a positive correlation between the probability (number) of accidents and air pollution. In column (1), an increase of 1 μg/m^3 in the daily average of PM2.5 leads to an increase of approximately 0.12 % in the probability of claims within one day. In column (2) we find that an increase in the daily average of PM2.5 by 1 μg/m^3 is significantly associated with an increase in the number of claims by 0.40 %.[16] This is consistent with the literature arguing that air pollution affects health, impairs mental functions, and causes more car accidents than otherwise (Anstey, Wood, Lord, & Walker, 2005; Badman & Jaffe, 1996; He, Fan, & Zhou, 2016; Sager, 2019). Air pollution, on the other hand, has the opposite effect on the severity of accidents. As shown in column (3) and column (4), a 1 μg/m^3 increase in PM2.5 is associated with a 0.01 % decrease in the average claim ratio and a 0.68 % decrease in the average claim amount. The reduction in the claim ratio is approximately 1.20 % of its mean value.[17] In terms of monetary value, the coefficient for the average claim amount is equivalent to 26.23 yuan.[18] Considering that insurance claim amounts are a proxy for accident severity, the above results suggest that when air pollution is severe, people are likely to be more cautious than usual, resulting in a decrease in the severity of accidents. When considering both the number of claims and average claim amount effects of air pollution, we find that for every increase of 1 μg/m^3 in PM2.5, the district daily claim amount decreases by approximately 33.54 yuan.[19] This suggests that being cautious while driving can effectively reduce the adverse effects of air pollution. In order to gain insights into the comprehensive impact of air pollution on traffic accidents, we utilize the logarithm of the total claim amount in district i on day t as the dependent

[14] We adopt the radius selection criteria employed by Chen et al. (2021).

[15] To alleviate potential endogeneity concern, we employ the IV approach in all analyses, in addition to the OLS estimation reported in Panel A and the categorical measure of the PM2.5 reported in Panel C of Table 2.

[16] The estimated coefficient in Column (2) of Table 2 is 0.0040, which is equivalent to a percentage increase of 0.40 % ((eˆ0.0040–1) × 100). All subsequent percentage effect interpretations for which the dependent variable is the number of claims and the average claim amount follow the same formula.

[17] The mean average claim ratio is 0.801 %. In Column (3) of Table 2, the estimated coefficient of −0.0096 represents a 1.20 % decrease in the average claim ratio compared to its mean value, calculated as (−0.0096 / 0.801) × 100.

[18] The mean of average claim amount is 3869.97 yuan. In Column (4) of Table 2, the estimated coefficient of −0.0068 represents a 0.68 % decrease in the average claim amount, calculated as [(eˆ(−0.0068) - 1) × 100]. The monetary reduction in the average claim amount is calculated as 3869.97 × (eˆ(−0.0068) - 1).

[19] The mean number of claims is 3.09. For every 1 μg/m^3 increase in PM2.5 concentration, the number of claims increases by 0.40 %, while the average claim amount decreases by 26.23 yuan. The district-day claim amount is calculated by multiplying the number of claims by the average claim amount. Therefore, when air pollution (PM2.5) increases by 1 μg/m^3, the change in claim amount can be calculated as: [(3.09 + (3.09 × 0.4 %)) × (3869.974–26.23)] - (3.09 × 3869.974).

Table 2
Baseline: the impact of air pollution on traffic accidents.

	(1)	(2)	(3)	(4)
Variables	claims status	number of claims	claim ratio	claim amount
Panel A: OLS				
PM25	0.0001***	0.0001*	−0.0005***	−0.0003*
	(4.78)	(1.66)	(−2.86)	(−1.94)
R-squared	0.516	0.750	0.323	0.334
Panel B: IV				
1st stage				
Inversion strength	−5.7747***	−6.5846***	−6.5846***	−6.5846***
	(−8.51)	(−7.05)	(−7.05)	(−7.05)
F test (K—P)	169.576	33.372	33.372	33.372
2nd stage				
PM25	0.0012**	0.0040*	−0.0096***	−0.0068**
	(2.11)	(1.80)	(−2.92)	(−2.30)
Panel C: non-linear				
group2	0.0042**	0.0033	−0.0208*	−0.0161
	(2.24)	(0.57)	(−1.76)	(−1.48)
group3	0.0065**	0.0137	−0.0369**	−0.0269*
	(2.26)	(1.64)	(−2.19)	(−1.73)
group4	0.0033	0.0186*	−0.0517**	−0.0348*
	(0.85)	(1.66)	(−2.30)	(−1.67)
R-squared	0.516	0.750	0.323	0.334
Observations	346,323	82,897	82,897	82,897
control	YES	YES	YES	YES
day-of-week FE	YES	YES	YES	YES
year-by-week-by-district FE	YES	YES	YES	YES
cluster	district date	district date	district date	district date

This table presents the impact of air pollution on traffic accidents. Panel A reports the OLS estimates of eq. (1), Panel B reports the 2SLS estimates of eqs. (3) and (4), and Panel C reports the categorical OLS estimates of eq. (2). Panel B uses the strength of atmospheric temperature inversion (temperature difference between the second and the first layers) as the instrument for PM2.5. Columns (1), (2), (3), and (4) report the results for the claim status, number of claims, average claim ratio, and average claim amount. All regressions control for temperature, dew point temperature, wind speed, precipitation, visibility, and three weather dummy variables for fog, rain, and snow. Robust t-statistics in parentheses are robustly two-way clustered at the district-day level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

variable.[20] The results are presented in Table A.1, with Panel A showing the regression results and Panel B providing descriptive statistics regarding the variables. The results indicate that a 1 μg/m^3 increase in PM2.5 concentration correlates with an average decrease of 0.33 % in total claim amounts, equivalent to a reduction of 32.11 yuan daily.[21] This is consistent with the conclusion drawn from an integrated analysis of air pollution's separate impact on the number of accidents and the average claim amount.

We examine the nonlinear influence of PM2.5 on traffic accidents by including PM2.5 as a categorical variable in Panel C of Table 2. The literature discusses the nonlinear effects of air pollution, which arise because individuals' responses to severe air pollution (the highest category) are disproportionally higher than their responses to lower levels of pollution (Chen et al., 2021; Chen, Guo, & Huang, 2018; Qin et al., 2019; Qin & Zhu, 2018). Therefore, we follow the literature and decompose the continuous PM2.5 level into four bins, with cutoffs of 35, 75, and 115, which represent excellent, good, lightly polluted, and moderately polluted and above air quality, respectively (where the final category or bin combines the moderately, heavily, and severely polluted categories). As shown in Panel C, the effect becomes disproportionally larger as the PM2.5 level increases: the magnitude of the coefficients increases with the air pollution level, indicating the nonlinear effect of air pollution on the probability, number, and severity of accidents within one day. Specifically, compared with the base group (which has a PM2.5 level of less than 35, or excellent air quality), the daily number of accidents increased by 1.87 %, and the average claim ratio and claim amount decreased by 0.05 % and 3.42 %, respectively, if PM2.5 reach moderately polluted or above levels.

Figure 4 shows the coefficient estimates and 95 % confidence intervals for the PM2.5 category indicators on probability, number,

[20] While the total claim amount reflects the overall impact of the changes, it does not identify the specific causes of the changes. For example, a high total claim amount on a given day may result from either a single severe accident with a large payout or multiple minor accidents with cumulatively high claims. In our subsequent analysis, we focus on the number of claims and average claim amount. This differentiation between accident frequency and severity is crucial as it gives us a more nuanced understanding of how air pollution affects traffic accidents.

[21] The mean amount of the total claim is 9746.30 yuan. In Panel A of Table A.1, the estimated coefficient of −0.0033 represents a 0.33 % decrease in the average claim amount, calculated as [(eˆ(−0.0033) - 1) × 100]. The monetary reduction in the total claim amount is calculated as 9746.30 × (eˆ(−0.0033) - 1).

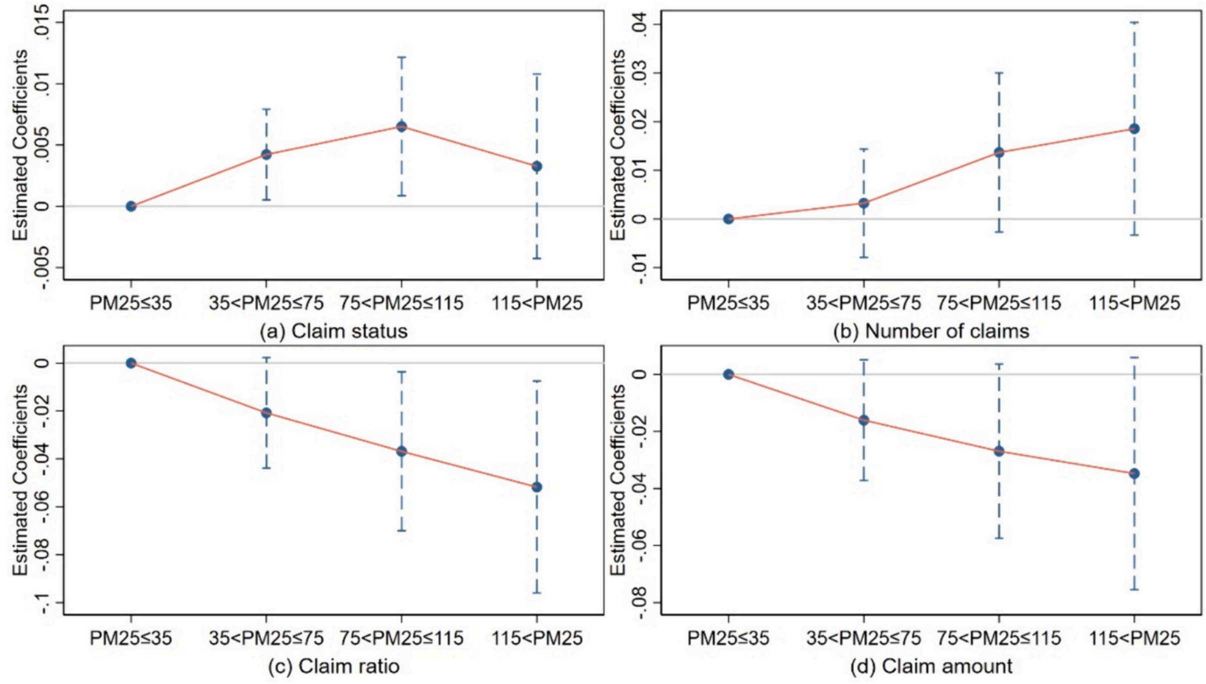

Fig. 4. Outcome variables in Each PM2.5 category relative to that on excellent days.
This figure shows the coefficient estimates for the PM2.5 category indicators and the 95 % confidence intervals. The numbers indicate the estimated coefficients on days in each of the three PM2.5 categories relative to those made on excellent PM2.5 days. Panel (a) shows the non-linear effects on claim status, Panel (b) shows the non-linear effects on the number of claims, Panel (c) shows the non-linear effects on average claim ratio, and Panel (d) shows the non-linear effects on average claim amount, respectively.

average claim ratio, and average claim amount of accidents, which exhibit an approximate monotonous pattern. There is a noticeable increase in claims (decrease in average claim ratio and average claim amount) when air pollution reaches moderate levels and beyond (which has a PM2.5 level greater than 115), in contrast to lower levels. This finding demonstrates that air pollution has a non-linear positive impact on the probability and number of claims, as well as a non-linear negative effect on average claim ratios and average claim amounts.

As we observe an increase in the probability and number of claims and a decrease in the average claim ratio and amount on polluted days, we can infer that pollution has a negative effect on road safety, but drivers' caution can mitigate this effect. We further investigate drivers' caution by examining the reductions in the average claim ratio and average claim amount for accidents of different degrees of severity. Fig. 5 plots the quantile regression results. The coefficients are negative in all quantiles, with quantiles beyond 60 % exhibiting more negative coefficients, indicating a reduction in the severity of accidents at all levels, especially in serious accidents.

Now, we conduct a set of robustness checks. First, we use the AQI as an alternative measure of air quality to replicate the findings in Table 2.[22] The estimated results, shown in Panel A of Table 3, are very similar to those using PM2.5. For every 1 unit increase of AQI, the probability and the number of accidents within one day increase by 0.12 % and 0.55 %, respectively, the claim ratio and the claim amount of accidents decrease by 0.01 % and 0.43 %, respectively. We also employ alternative pollutants (e.g., O3, SO2) as measures for air pollution, and the results in Table A.2 indicate that the effect of air pollution on traffic accidents is robust.

Second, air pollution may be related to weather and temperature, which may affect the number of accidents and their severity. The previous regression model that we employed includes weather patterns linked to road traffic accidents, such as temperature, dew point temperature, wind speed, precipitation, visibility, and three weather dummy variables for fog, rain, and snow. However, there may be a more complicated relationship between temperature and traffic accidents than is reflected in this regression model. Therefore, we add a fourth-degree polynomial of ground temperature and re-run the main regressions to ensure that false correlations with temperature do not drive our results. The Panel B of Table 3 describes the impact of air pollution on traffic accidents after adding the fourth-degree polynomial for ground temperature. Even after accounting for fourth-degree polynomial temperature factors, the increase in the PM2.5 level is associated with an increased probability and number of claims, as well as a decreased average claim ratio and average claim amount.

Third, we supplement our results by using a subsample from which we remove the observations for accidents that take place outside

[22] It is worth noting the concern that some cities may underreport or manipulate their AQI, which could potentially result in biased estimates (Chen, Jin, Kumar, & Shi, 2012).

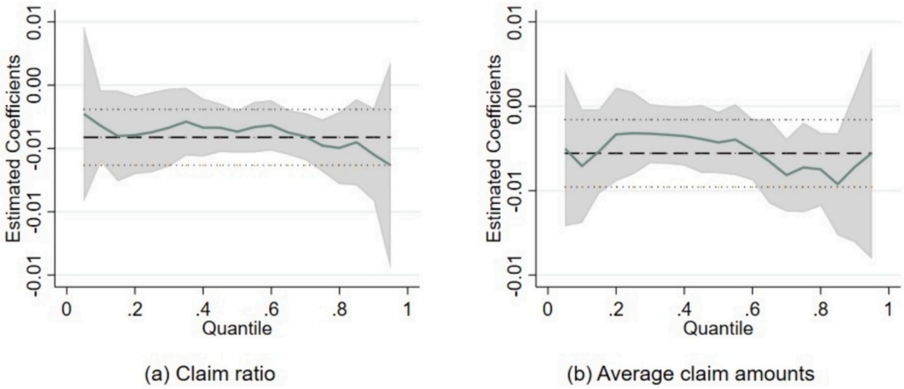

Fig. 5. Quantile regression—impact of air pollution on accident severity.
This figure plots the estimated coefficient and the 95 % confidence intervals of the quantile regression under the claim amount specification, showing how the average claim ratio at different quantiles is affected by air pollution in Panel (a) and how the average claim amount at different quantiles is affected by air pollution in Panel (b). It illustrates how the severity of car accidents changes with air quality changes.

the province where the insurance contract is taken out.[23] One concern is that the unfamiliarity of out-of-town drivers with road conditions may lead to more accidents than is the case for drivers who are more familiar with the road conditions. Therefore, we only keep those accidents that occurred locally, and re-estimate the main specification. The results are shown in the Panel C of Table 3. Using the 2SLS method, the results reveal significant associations between PM2.5 levels and various aspects of accidents. Specifically, for each 1 μg/m^3 increase in PM2.5, the probability of accidents increases by 0.12 %, and the daily number of accidents rises by 0.39 %. Furthermore, there is a 0.01 % decrease in the average claim ratio and a 0.53 % decrease in the average claim amount for accidents.

In addition, although we have considered the impact of weather conditions on accidents in the baseline specification, we note that rain or snow can affect driving behavior and accidents (Sager, 2019). Therefore, we employ a subsample that includes only days on which total precipitation is below 0.5 mm,[24] which means that both rain and snow are much less likely to drive a change in claim numbers and claim amounts on these days compared with others. As shown in columns (1) and (2) in Panel D of Table 3, there is a positive impact of air pollution on the probability and number of accidents excluding the effects of precipitation. Columns (3) and (4) in Panel D of Table 3 show the impact of air pollution on the average claim ratio and claim amount in the low precipitation subsample, and all the results support air pollution having a significant negative effect on the severity of the accidents.

We also include the PM2.5 concentrations in the three previous days in the regression equation as additional controls to exclude the impact of lagged air pollution. As shown in Panel E of Table 3, only same-day air pollution has impacts on accidents. This implies that the effects of air pollution on the probability, number, and severity of accidents are not influenced by lagged pollution.

Next, we perform additional robustness checks by substituting other instrumental variables to validate the impact of air pollution on traffic accidents. Two alternative instruments are employed in the estimation process. Firstly, we can refer to Barwick et al. (2018) and Chen et al. (2021) and use upwind pollution, which is constructed based on wind direction and wind speed, as an instrumental variable to re-estimate the results presented in Panel B of Table 2. The second instrumental variable is derived from Bondy et al. (2020), which incorporates both the atmospheric temperature inversion and the upwind pollution to measure pollution. It can be seen from Table 4 that all specifications indicate positive impacts of pollution on the probability and number of accidents and negative effects on the average claim ratio and claim amount.[25]

We also present separate results for alternative functional forms. Probit models are commonly used when the dependent variable is a binary dummy variable. Using the Probit model with instrumental variables, we estimate the impact of air pollution on the probability of accidents. Furthermore, the Poisson model is often utilized to explore factors affecting accident counts. We apply the control function approach to estimate the impact of air pollution on accident count under a Poisson model with pseudo maximum likelihood (PPML) based on the work of Shr et al. (2023). Specifically, we estimate two forms of counts: excluding zero counts and including zero

[23] Despite restricting our sample to accidents that occurred within five specific provinces and cities—Beijing, Shanghai, Inner Mongolia Autonomous Region, Shandong, and Sichuan—there remains a very small fraction of accidents that occurred outside the province where the insurance contracts were signed, such as signing a contract in Beijing but having the accident occur in Inner Mongolia. More than 99 % of the accidents in our sample had occurred in the same province where the insured party signed the contract.

[24] 0.5 mm is approximately 0.0197 in..

[25] To address concerns that our IV strategy may not fully account for the impact of omitted traffic volume, we conduct two additional analyses: (1) We examine the impact of air pollution on accidents across different contexts with varying traffic volumes and patterns (e.g., weekdays vs. weekends, rush vs. non-rush hours, areas with differing road and population densities). No significant differences are found, suggesting that traffic volume does not substantially influence our main results. (2) Based on Sager (2019) and Shr et al. (2023), we replicate the results from the baseline specifications and Table 10 using different fixed effects strategies to account for variations in traffic conditions. The results remain robust, further mitigating concerns about the influence of traffic volume. These additional analyses are not reported in the main text for brevity but are available upon request.

Table 3
Robustness: alternative measure, samples, and control variables.

	(1)	(2)	(3)	(4)
Variables	claims status	number of claims	claim ratio	claim amount
Panel A: AQI				
AQI	0.0012**	0.0055*	−0.0070***	−0.0043**
	(2.05)	(1.93)	(−2.68)	(−2.14)
Observations	346,323	82,897	82,897	82,897
F test (K—P)	94.312	25.114	25.114	25.114
Panel B: 4th-degree polynomial				
PM25	0.0016**	0.0040*	−0.0014*	−0.0011**
	(2.06)	(1.81)	(−1.74)	(−2.39)
Observations	346,323	82,897	82,897	82,897
F test (K—P)	164.707	30.375	35.379	30.375
Panel C: local				
PM25	0.0012**	0.0039*	−0.0095*	−0.0053**
	(2.20)	(1.95)	(−1.79)	(−2.33)
Observations	344,654	82,246	82,246	82,246
F test (K—P)	260.406	70.852	70.852	70.852
Panel D: low precipitation				
PM25	0.0016*	0.0058*	−0.0075**	−0.0040*
	(1.71)	(1.95)	(−2.57)	(−1.87)
Observations	213,667	45,983	45,983	45,983
F test (K—P)	89.526	38.824	38.824	38.824
Panel E: lag				
PM25 (3 days before)	−0.0001	−0.0001	−0.0003	−0.0002
	(−1.44)	(−0.66)	(−1.31)	(−1.15)
PM25 (2 days before)	0.0000	−0.0002	0.0004	0.0004
	(0.23)	(−1.40)	(1.37)	(1.65)
PM25 (1 day before)	−0.0000	−0.0002	−0.00006	−0.0002
	(−0.38)	(−1.39)	(−0.17)	(−0.51)
PM25	0.0004*	0.0035**	−0.0034***	−0.0074**
	(1.78)	(2.20)	(−2.85)	(−2.26)
Observations	342,978	82,052	82,052	82,052
F test (K—P)	225.051	41.866	41.839	41.866
Control	YES	YES	YES	YES
day-of-week FE	YES	YES	YES	YES
year-by-week-by-district FE	YES	YES	YES	YES
cluster	district date	district date	district date	district date

This table presents the impact of air pollution on traffic accidents using alternative measures of air pollution (AQI), different subsamples, and additional control variables. The IV is the strength of atmospheric temperature inversion (temperature difference between the second and the first layers). Panel A reports the results using the AQI as an alternative measure of air quality, Panel B reports the results incorporating the fourth-degree polynomial for ground temperature as control variables, Panel C reports the results using a subsample excluding out-of-town accidents, Panel D reports the results using the low precipitation sample, and Panel E reports the results incorporating the PM2.5 concentrations in the three previous days in regression models. Columns (1), (2), (3), and (4) report the results for the claim status, number of claims, average claim ratio, and average claim amount. All regressions control for temperature, dew point temperature, wind speed, precipitation, visibility, and three weather dummy variables for fog, rain, and snow. Robust t-statistics in parentheses are robustly two-way clustered at the district-day level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

counts. Table A.3 provides estimates from these alternative specifications, illustrating that air pollution increases both the probability and the number of accidents.

Then, we use claim percentage as an alternative to the number of claims to address concerns regarding variations in the insurance company's market penetration rates across districts. Due to the constraint that we are only able to identify the province to which the insurance contract belongs, we calculate the claim percentage by dividing the daily number of claims by the number of insured individuals at the provincial level on that particular day (assuming Beijing and Shanghai as provincial administrative units). As shown in Table A.4, elevated air pollution increases the claim percentage, partially mitigating the concern.

Finally, as a falsification test, we extract the PM2.5 in the sample and randomly distribute them to each observation following

Table 4
Robustness: alternative measures of IV.

	(1)	(2)	(3)	(4)
Variables	claims status	number of claims	claim ratio	claim amount
Panel A: Wind IV				
1st stage				
Upwind PM2.5	38.1009***	41.4547***	41.4547***	41.4547***
	(101.78)	(66.52)	(66.52)	(66.52)
F test (K—P)	162.406	301.397	301.397	301.397
2nd stage				
PM25	0.0012*	0.0038**	−0.0071**	−0.0093***
	(1.81)	(2.07)	(−2.00)	(−2.65)
Panel B: Both IV				
1st stage				
Upwind PM2.5	37.1613***	40.3643***	40.3643***	40.3643***
	(99.90)	(65.34)	(65.34)	(65.34)
Inversion strength	−4.0821***	−4.4152***	−4.4152***	−4.4152***
	(−47.92)	(−22.32)	(−22.32)	(−22.32)
F test (K—P)	101.440	160.123	160.123	160.123
2nd stage				
PM25	0.0012**	0.0042***	−0.0063*	−0.0072**
	(2.14)	(2.74)	(−1.93)	(−2.48)
Observations	346,323	82,897	82,897	82,897
control	YES	YES	YES	YES
day-of-week FE	YES	YES	YES	YES
year-by-week-by-district FE	YES	YES	YES	YES
cluster	district date	district date	district date	district date

This table presents the impact of air pollution on traffic accidents. Panel A reports the 2SLS estimates using the upwind pollution as an instrument, Panel B reports the 2SLS estimates using both the upwind pollution and the strength of atmospheric temperature inversion (temperature difference between the second and the first layers) as the instrument for PM2.5. Columns (1), (2), (3), and (4) report the results for the claim status, number of claims, average claim ratio, and average claim amount. All regressions control for temperature, dew point temperature, wind speed, precipitation, visibility, and three weather dummy variables for fog, rain, and snow. Robust t-statistics in parentheses are robustly two-way clustered at the district-day level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Cornaggia and Li (2019). We then re-estimate the effects of air pollution using a random PM2.5 indicator, further supporting our claim that our finding is not due to a mechanical correlation between the unobservable district-day level factors and road safety. Table A.5 provides these results.

4.2. Unexpected and persistent air pollution

In this subsection, we explore how accident probability, numbers, and severity are affected by unexpected air pollution, which captures the extent to which an area experiences unusually bad air quality conditions, and persistent air pollution, which captures an extended period of air pollution.

In Panel A of Table 5, we report the estimations for the effect of unexpected pollution on the probability and number of claims involved in accidents, as well as the average claim ratio and claim amount. We define the weekly average pollution experienced by the same district before the accident as the level of pollution that can be expected. Then, we define unexpected pollution as pollution that exceeds this anticipated level.[26]

As shown in columns (1) and (2) in Panel A of Table 5, the unexpected pollution leads to a 0.09 % increase in the probability of traffic accidents and a 0.32 % increase in the number of claims within one day for every 1 $\mu g/m^3$ change in the PM2.5, which is lower than results of the baseline regression (0.12 % and 0.40 %, as shown in columns (1) and (2) in Panel B of Table 2). Columns (3) and (4) in Panel A of Table 5 show that the magnitude of the effects of unexpected air pollution on the average claim ratio and claim amount are slightly higher than the effect of real-time pollution. Specifically, for every increase of 1 $\mu g/m^3$ in unexpected PM2.5, the average claim ratio experiences a decrease of approximately 1.77 % of its mean value, along with a monetary decrease of 26.34 yuan in the average claim amount. One possible explanation is that when people notice that pollution is more severe than they expected, they drive more cautiously, which reduces part of the increase in the number of accidents caused by air pollution and leads to less serious car

[26] Giroud, Mueller, Stomper, and Westerkamp (2012) use unexpected snow to represent the difference between the current year and previous years' conditions; our definition of unexpected air pollution, defined as the difference between the air pollution at the time of the accident and pollution before the accident (the level of pollution that drivers would expect), is similar.

Table 5
Impact of unexpected and persistent air pollution.

	(1)	(2)	(3)	(4)
Variables	claims status	number of claims	claim ratio	claim amount
Panel A: unexpected pollution				
unexpected PM25	0.0009**	0.0032*	−0.0142***	−0.0068***
	(2.18)	(1.88)	(−3.53)	(−2.64)
F test (K—P)	443.998	83.082	83.082	83.082
Panel B: persistent pollution				
PM25	0.0001	0.0015	−0.0071	−0.0045*
	(0.22)	(0.89)	(−1.55)	(−1.87)
persistent*PM25	−0.0001	−0.0014	0.0043	0.0033
	(−0.24)	(−1.03)	(1.38)	(1.35)
persistent	0.0117	0.0922	−0.3359	−0.2701
	(0.57)	(0.83)	(−1.23)	(−1.35)
F test (K—P)	142.334	18.243	18.243	18.243
Observations	345,015	82,310	82,310	82,310
control	YES	YES	YES	YES
day-of-week FE	YES	YES	YES	YES
year-by-week-by-district FE	YES	YES	YES	YES
cluster	district-date	district-date	district-date	district-date

This table presents the impact of unexpected and persistent air pollution on traffic accidents. Panel A reports the results for unexpected air pollution and Panel B reports the results for persistent air pollution. The IV is the strength of atmospheric temperature inversion (temperature difference between the second and the first layers). Columns (1), (2), (3), and (4) report the results for the claim status, number of claims, average claim ratio, and average claim amount. *Unexpected PM25* equals the difference between pollution concentration on the day of a traffic accident and the average pollution concentration of the past week. *Persistent* is an indicator variable that equals one if more than half of the prior week before the traffic accident has unhealthy PM2.5 values (i.e., PM2.5 > 75), and zero otherwise. All regressions control for temperature, dew point temperature, wind speed, precipitation, visibility, and three weather dummy variables for fog, rain, and snow. Robust t-statistics in parentheses are robustly two-way clustered at the district-day level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

accidents.

The effect of air pollution on accidents may become more pronounced when there has been an extended period of air pollution. Thus, we include a measure of persistent pollution and examine its interaction terms with the air pollution variable as additional regressors in Eq. (4). Following Huang, Xu, and Yu (2020), we define persistent pollution days as those for which more than half of the prior week has unhealthy PM2.5 values (i.e., PM2.5 > 75).[27] we show in Panel B of Table 5 that the effect of persistent pollution on accidents is insignificant.

Next, we examine whether and to what extent previous pollution levels affect the accident situation in the current period using a polynomial distributed lag model, which can mitigate the concern of multicollinearity across the lag terms of air pollution (Almon, 1965). We plot the lagged pollution coefficients in Fig. A.4. We can observe from this figure that the coefficients are not statistically significant across all periods, further supporting the conclusion that air pollution exhibits no lagged effects on traffic accidents.

4.3. Heterogenous treatment effect

Taking advantage of the richness of the data, we can explore the heterogeneity of the main results. Following Sager (2019), we first split the sample into "warm months" (May to October) and "cold months" (November to April),[28] to examine how people respond to pollution differently in different months. We incorporate the interaction term between "warm months" and PM2.5 in Eq. (4) to investigate seasonal differences. The results are presented in Table 6, where columns (1) and (2) illustrate the impact of air pollution on the probability and number of daily accidents. The findings indicate a significantly greater effect of air pollution on accidents during warm months. This may be because, in warm months, drivers are more likely to drive with open windows and thus are exposed to higher pollution levels than in colder months. Columns (3) and (4) showcase the effect of air pollution on the average claim ratio and claim amount. We observe a more pronounced negative correlation between air pollution and accident severity in warm months. It is possible that drivers are less able to assess the air quality under natural light during the cold months due to the shorter duration of sunlight. This visual assessment serves as an important channel influencing risky driving behaviors (Shr et al., 2023).

Previous research suggests that males are more risk-taking than females (see, e.g., Barsky, Juster, Kimball, & Shapiro, 1997; Charness & Gneezy, 2012; Faccio, Marchica, & Mura, 2016; Sundén & Surette, 1998). We further investigate how different genders respond to pollution differently. The results from Table 7 indicate that the influence of air pollution on driving behaviors does not exhibit significant differences between males and females. However, upon further segregating the sample by gender into male and

[27] Huang et al. (2020) define AQI exceeding 100 as an unhealthy pollution level. Correspondingly, we utilize a threshold of 75 for PM2.5, distinguishing between lightly polluted and good air quality.

[28] Sager (2019) defines "warm months" as June through September and the other months are "cold months." We adjust the range of warm months and "cold months" according to the Chinese situation.

Table 6
Heterogeneous treatment: warm(May to October)or cold month.

	(1)	(2)	(3)	(4)
VARIABLES	claims status	number of claims	claim ratio	claim amount
PM25	0.0003	0.0096***	−0.0053*	−0.0020
	(0.75)	(3.79)	(−1.91)	(−0.71)
warm*PM25	0.0012**	0.0055**	−0.0058*	−0.0090***
	(2.06)	(2.46)	(−1.71)	(−3.01)
warm	−0.0344	−0.3905***	0.3223*	0.4955***
	(−1.14)	(−3.07)	(1.73)	(2.94)
Observations	346,323	82,897	82,897	82,897
F test (K—P)	211.249	49.926	49.899	49.926
control	YES	YES	YES	YES
day-of-week FE	YES	YES	YES	YES
year-by-week-by-district FE	YES	YES	YES	YES
cluster	district date	district date	district date	district date

This table presents the heterogeneity of air pollution (PM2.5) impact on traffic accidents in cold and warm months. The warm months are from May to October. *warm* is 1 if in the warm months; otherwise, it is 0. The IV is the strength of atmospheric temperature inversion (temperature difference between the second and the first layers). Columns (1), (2), (3), and (4) report the results for the claim status, number of claims, average claim ratio, and average claim amount. All regressions control for temperature, dew point temperature, wind speed, precipitation, visibility, and three weather dummy variables for fog, rain, and snow. Robust t-statistics in parentheses are robustly two-way clustered at the district-day level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7
Heterogeneous treatment: by gender.

	(1)	(2)	(3)
VARIABLES	number of claims	claim ratio	claim amount
PM25	0.0101	−0.0147***	−0.0060**
	(1.38)	(−2.84)	(−2.08)
gender*PM25	−0.0016	0.0025	0.0001
	(−1.01)	(1.21)	(0.09)
gender	−0.1009	−0.0460	0.0600
	(−1.03)	(−0.37)	(0.82)
Observations	101,838	101,838	101,838
F test (K—P)	79.906	79.906	79.906
control	YES	YES	YES
day-of-week FE	YES	YES	YES
year-by-week-by-district FE	YES	YES	YES
cluster	district date	district date	district date

This table presents the heterogeneity of air pollution (PM2.5) impact on traffic accidents for males and females. If the *gender* is male, the value is 1; otherwise, it is 0. The IV is the strength of atmospheric temperature inversion (temperature difference between the second and the first layers). Columns (1), (2), and (3) report the results for number of claims, average claim ratio, and average claim amount. All regressions control for temperature, dew point temperature, wind speed, precipitation, visibility, and three weather dummy variables for fog, rain, and snow. Robust t-statistics in parentheses are robustly two-way clustered at the district-day level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

female subgroups, there is some evidence supporting the idea that females are more risk-averse. Estimates presented in column (1) of Table A.6 suggest that the impact of pollution on the number of claims is more significant for males than for females. From columns (2) and (3) of Table A.6, we observe that air pollution has a larger impact on reducing the average claim ratio and claim amount for females compared to males. This concurs with studies indicating that women typically have higher risk awareness than men and are more cautious about air pollution than men (see, e.g., Croson & Gneezy, 2009; Jin, Andersson, & Zhang, 2020; Lerner, Gonzalez, Small, & Fischhoff, 2003). Taken together, although air pollution has a heterogeneous effect on different gender groups, the statistical difference is minimal.

We are also interested in whether the effects of air pollution are heterogeneous across age groups. Following Sager (2019), we generate three age groups based on drivers' age: 18 to 29 years old,[29] 30 to 45 years old, and more than 45 years old.[30] In column (1) of Table 8, we report the impact of air pollution on the number of accidents and find that the effect is strongest for the oldest drivers and becomes smaller for the younger age cohorts. Substantial evidence shows that elderly people are particularly vulnerable to air

[29] In China, only adults who are over 18 years old can drive motor vehicles.

[30] According to data from the MPS of the People's Republic of China, the predominant age range for Chinese drivers is between 26 and 50 years old. To ensure sufficient observations in each category and eliminate potential result ambiguity arising from sample size discrepancies, we modify the age group cutoffs. Notably, adopting the grouping methodology employed by Sager (2019) yield consistent results.

Table 8
Heterogeneous treatment: by age.

	(1)	(2)	(3)
VARIABLES	number of claims	claim ratio	claim amount
PM25	0.0032	0.0040**	0.0049***
	(1.11)	(2.34)	(3.32)
age(26–45)*PM25	0.0013***	−0.0045**	−0.0048***
	(2.68)	(−2.27)	(−2.66)
age(≥ 46)*PM25	0.0014**	−0.0061**	−0.0054***
	(2.53)	(−2.50)	(−2.67)
age(26–45)	−0.1123***	0.3088**	0.3106***
	(−3.60)	(2.57)	(2.86)
age(≥ 46)	−0.0841**	0.3801**	0.3066**
	(−2.46)	(2.57)	(2.48)
Observations	120,781	120,781	120,781
F test (K—P)	40.867	40.853	40.867
control	YES	YES	YES
day-of-week FE	YES	YES	YES
year-by-week-by-district FE	YES	YES	YES
cluster	district date	district date	district date

This table presents the heterogeneity of air pollution (PM2.5) impact on traffic accidents of different ages. There are three groups: 18 to 29 years old, 30 to 45 years old, and more than 45 years old. *Age(26–45)* is 1 if the driver's age falls between 26 and 45 years old; otherwise, it is 0. *age(≥ 46)* is 1 if the driver is more than 45 years old; otherwise, it is 0. The IV is the strength of atmospheric temperature inversion (temperature difference between the second and the first layers). Columns (1), (2), and (3) report the results for number of claims, average claim ratio, and average claim amount. All regressions control for temperature, dew point temperature, wind speed, precipitation, visibility, and three weather dummy variables for fog, rain, and snow. Robust t-statistics in parentheses are robustly two-way clustered at the district-day level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

pollution because they tend to have multiple long-term conditions, such as high blood pressure, diabetes, and heart disease (He et al., 2016). Columns (2) and (3) of Table 8 show the impact of air pollution on average claim ratio and average claim amount for different age groups. We find that the effect is strongest for drivers aged above 45 years old. As risk aversion tends to increase with age, older people exhibit greater caution in their driving behavior, resulting in a greater decrease in the average claim ratio and claim amount when air pollution increases compared with drivers younger than 29 years old. Overall, while older people may be more vulnerable to cognitive impairment caused by air pollution, their lower risk appetite allows them to mitigate some adverse consequences and reduce the severity of accidents.[31]

5. Discussion: risk preferences and avoidance behaviors

We show that as the air pollution level increases, the probability and number of accidents increase; however, the average claim ratio and average claim amount decrease. People in environments with poor air quality behave more conservatively than those in less polluted areas (Chang et al., 2018), and they tend to purchase air purifiers or wear masks to take protective measures against air pollution (Ito & Zhang, 2020; Zhang & Mu, 2018). In this section, we further explore the underlying mechanisms through which air pollution influences the severity of accidents from the perspectives of the drivers' risk preferences and avoidance behaviors.

We are fortunate that our data source of claim records contains the amount of insurance coverage for each insurance contract. Auto insurance in China is divided into compulsory auto liability insurance and other types of auto insurance (commonly referred to as "commercial" auto insurance). The compulsory auto liability insurance (which generally include third-party death and injury other than passengers and the driver, and medical and vehicle damage) is well-known to consumers, and they are compulsory for both private and commercial use vehicles. Commercial auto insurance (which covers all related claims that are not covered by compulsory auto liability insurance) is optional, enabling car owners to opt for commercial insurance beyond the coverage of a compulsory policy. The compulsory auto liability insurance policy provides only a predetermined minimum level of coverage, so many vehicle owners choose to purchase commercial insurance to extend their coverage, allowing a more flexible selection of coverage types and amounts. The decision to purchase high-coverage auto insurance may indicate that a driver is risk-averse. It indicates a higher sense of financial

[31] This result could also be attributed to our grouping of drivers aged 45 and above as the eldest age group, where drivers are very likely to be in good health. The impairment of cognitive ability caused by air pollution has not yet reached a level severe enough to prevent them from driving cautiously. Within the entire sample of accidents, drivers aged 60 and above only make up 1.83 %. The limited sample size of older drivers prevents us from establishing a dedicated cohort to investigate the impact of air pollution on the elderly.

security and protection from potential losses, even at the expense of an increased premium. In addition, the premium of compulsory auto liability insurance varies depending on the policyholder's behavior and record: drivers who are responsible may benefit from a discounted premium, while those who have committed traffic violations are subject to a higher premium.[32] In our sample, we can observe the amount of commercial auto insurance coverage and the compulsory auto liability insurance premium. Thus, we measure the driver's risk preference by observing the amount of commercial auto insurance coverage as well as the premium associated with compulsory auto liability insurance.[33] Moreover, while an accident may be incidental, multiple accidents within the same insurance period may indicate that the driver is engaging in risky driving behavior. Therefore, we also use drivers' claim history to estimate their risk preferences.

In particular, we classify drivers with a higher or equal commercial coverage amount than the median, with a compulsory liability insurance premium below the state's base premium, and with only one recorded accident as risk-averse. As for others, they are classified as risk-taking. For the risk-taking group, the variable *risk* is 1, otherwise is 0. We calculate the average claim ratio and average claim amount separately for each group. The control variables and fixed effects are the same as those in the baseline specification.

Columns (1) and (2) of Table 9 show the regression results with the commercial coverage amount as the risk appetite measure. The interaction of PM2.5 and insurance coverage has a negative impact on both the average claim ratio and claim amount, which is significant at the 1 % level. Columns (3) and (4) of Table 9 report the results of using compulsory auto liability insurance premiums as a risk appetite measure. The interaction between PM2.5 and premium has a negative impact on the average claim ratio and claim amount, a result that is significant at the 5 % or above level. Columns (5) and (6) of Table 9 present the results with historical accidents as the risk appetite measure. The interaction term of PM2.5 and the claim times has a negative impact on the average claim ratio and claim amount, with this effect being statistically significant at the 1 % level. In other words, car owners who are more risk-averse and cautious than other drivers will be more careful when air pollution occurs, so their average claim ratio and average claim amount will decrease more than the other group.[34]

Drivers may also engage in avoidance behaviors in response to high levels of air pollution. We would anticipate significant differences in the impact of air pollution on the severity of traffic accidents during periods with varying traffic volume in responses to pollution if the negative effect of air pollution on the severity of accidents is due to a reduction in traffic volume caused by avoidance behavior. For instance, it has been documented that elevated levels of air pollution limit outdoor activities (e.g., Graff Zivin & Neidell, 2009; Janke, 2014; Saberian, Heyes, & Rivers, 2017) as well as discretionary trips (Cutter & Neidell, 2009). Therefore, periods with a higher proportion of discretionary trips (e.g., non-rush hours and weekends) may exhibit a more significant decrease in traffic volume in response to air pollution, as compared to periods with a lower proportion of discretionary trips (e.g., commuting hours), during which air pollution would have a more significant negative impact on the severity of accidents. Based on Shr et al. (2023), we investigate whether the changes in traffic volume resulting from drivers' avoidance behavior could contribute to accident severity. Specifically, we examine whether the effects of air pollution are different for accidents that occur in on weekdays vs. weekends, rush vs. non-rush hours, and in regions with different road densities and population densities.

In particular, to differentiate various avoidance behaviors, we define four dummy variables. The variable *Weekdays* equals 1 on regular workdays and 0 on public holidays and weekends. *Rush* is set to 1 for peak commuting hours (7 a.m. to 10 a.m. and 4 p.m. to 8 p.m.) and 0 for other times. *Road density* equals 1 for areas with road density at or above the sample median, and 0 for areas below. Similarly, *Pop density* is 1 for areas with population density at or above the sample median, and 0 otherwise.

The regression results are presented in Table 10. Panels A and B focus on the effect of air pollution on accident severity in various time frames (weekdays vs. weekends, and rush hours vs. non-rush hours, respectively). Panels C and D examine whether varying avoidance behaviors in areas with different road and population densities, induced by air pollution, are associated with varying degrees of a reduction in accident severity.[35] As shown in the findings, the interaction terms between PM2.5 and the dummy variables representing different time periods and geographical regions are not statistically significant in all specifications. This comprehensive analysis, which includes different time frames and geographical regions, confirms that the negative impact of air pollution on accident

[32] According to the "Regulation on Compulsory Traffic Accident Liability Insurance for Motor Vehicles," available at https://www.gov.cn/gongbao/content/2013/content_2305138.htm, compulsory auto liability insurance enforces uniform insurance clauses and basic premium rates, resulting in standardized insurance premium. In cases where the insured motor vehicle remains free of road traffic safety violations and accidents, the insurance company is mandated to decrease the premium rate for the following year. Conversely, if the vehicle has been involved in violations or accidents, an increase in the premium rate is warranted. The criteria for adjusting these rates are established collaboratively by the China Banking and Insurance Regulatory Commission and the public security department of the State Council.

[33] We do not discuss commercial auto insurance premiums, as these premiums are also linked to various other factors, including the coverage amount, the new car purchase price, depreciation, etc.

[34] We note that the coefficient on the risk-taking dummy is challenging to interpret due to potential correlations between the main effect and the interaction term. Following Li, Song, Xu, and Yi (2022), who faced a similar issue, we estimate separate models for subsamples of risk-taking and risk-averse drivers. Results in Table A.7 show that air pollution significantly reduces accident severity for the risk-averse group, but not for the risk-taking group. Hausman's test confirms a significant difference in accident severity between the two groups due to air pollution.

[35] The data on population density is obtained from the National Bureau of Statistics, which provides information only at the city-year level. As a result, the regression coefficient for the variable *Pop density* has been omitted due to the need for granular data. In addition, we utilize cross-sectional data on population density from the Resource and Environmental Science Data Platform for the year 2015 to calculate the cross-sectional population density at the district level. This alternative dataset provides results that are consistent with our main findings. The main text does not include additional findings to maintain brevity but may be requested upon request.

Table 9
Mechanism: risk preference.

	Panel A: coverage		*Panel B: premium*		*Panel C: claim times*	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	claim ratio	claim amount	claim ratio	claim amount	claim ratio	claim amount
PM25	−0.0091***	−0.0073***	−0.0065**	−0.0053*	−0.0060*	−0.0057**
	(−3.01)	(−2.98)	(−2.13)	(−1.71)	(−1.96)	(−2.14)
risk*PM25	0.0086***	0.0049***	0.0089***	0.0059**	0.0076***	0.0072***
	(3.61)	(3.15)	(3.10)	(2.24)	(3.51)	(3.56)
risk	0.0850	−0.6623***	−0.7838***	−0.3156**	−0.5148***	−0.4347***
	(0.55)	(−6.85)	(−4.66)	(−2.06)	(−3.86)	(−3.45)
Observations	107,303	107,303	59,919	59,919	63,782	63,782
F test (K—P)	32.139	32.139	39.118	39.118	31.491	31.491
control	YES	YES	YES	YES	YES	YES
day-of-week FE	YES	YES	YES	YES	YES	YES
year-by-week -by-district FE	YES	YES	YES	YES	YES	YES
cluster	district date	district date	district date	district date	district date	district date

This table presents how air pollution and risk preference affect the accident severity. Panel A reports the results using commercial coverage amounts to classify drivers' risk preferences, Panel B reports the results using the compulsory liability insurance premium to classify drivers' risk preferences, and Panel C reports the results using claim history to classify drivers' risk preferences. If the driver is categorized in the risk-taking group, the variable *risk* is 1, otherwise is 0. The IV is the strength of atmospheric temperature inversion (temperature difference between the second and the first layers). Columns (1), (3), and (5) report the results for the average claim ratio. Columns (2), (4), and (6) report the results for the average claim amount. All regressions control for temperature, dew point temperature, wind speed, precipitation, visibility, and three weather dummy variables for fog, rain, and snow. Robust t-statistics in parentheses are robustly two-way clustered at the district-day level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10
Mechanism: avoidance behaviors.

	Panel A:Weekday vs. *Weekends*		*Panel B:Rush* vs. *Non-rush hour*		*Panel C:High* vs. *Low road density*		*Panel D:High* vs. *Low Pop density*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	claim ratio	claim amount	claim ratio	claim amount	claim ratio	claim amount	claim ratio	claim amount
PM25	−0.0048*	−0.0038**	−0.0050***	−0.0038**	−0.0068**	−0.0087***	−0.0091**	−0.0052*
	(−1.91)	(−2.35)	(−2.94)	(−2.40)	(−2.28)	(−4.90)	(−2.54)	(−1.89)
PM25*Weekdays	−0.0041	−0.0015						
	(−1.64)	(−1.01)						
Weekdays	0.0687	−0.0605						
	(0.45)	(−0.71)						
PM25*Rush hour			−0.0004	−0.0005				
			(−0.39)	(−0.44)				
Rush hour			−0.0159	−0.0935				
			(−0.24)	(−1.50)				
PM25*Road density					−0.0013	−0.0011		
					(−0.67)	(−0.64)		
Road density					0.1073	0.1163		
					(0.82)	(1.07)		
PM25*Pop density							−0.0005	−0.0021
							(−0.16)	(−0.93)
Pop density							–	–
Observations	82,897	82,897	113,045	113,045	98,823	98,823	80,883	80,883
F test (K—P)	68.293	68.293	49.801	49.801	54.352	54.352	22.620	22.620
control	YES	YES	YES	YES	YES	YES	YES	YES
day-of-week FE	YES	YES	YES	YES	YES	YES	YES	YES
year-by-week -by-district FE	YES	YES	YES	YES	YES	YES	YES	YES
cluster	district date	district date	district date	district date	district date	district date	district date	district date

This table presents how air pollution and avoidance behavior affect the accident severity across different temporal and spatial contexts. Panel A compares weekdays vs. weekends. Panel B contrasts rush hours vs. non-rush hours. Panel C examines regions with varying road densities. Panel D reports results for areas with different population densities. The IV is the strength of atmospheric temperature inversion (temperature difference between the second and the first layers). Columns (1), (3), (5), and (7) report the results for the average claim ratio. Columns (2), (4), (6), and (8) report the results for the average claim amount. All regressions control for temperature, dew point temperature, wind speed, precipitation, visibility, and three weather dummy variables for fog, rain, and snow. Robust t-statistics in parentheses are robustly two-way clustered at the district-day level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

severity cannot be attributed to the pollution-induced avoidance behavior. In addition, if air pollution changes the composition of drivers on the roads, with more risk-averse drivers present on high pollution days, it could potentially explain the negative impact of air pollution on accident severity. We investigate whether increased air pollution would affect the composition of drivers on the road (the share of traffic accidents involving male drivers, drivers under the age of 30, motorists aged 46 and older, and risk-averse drivers). Table A.8 in the appendix presents the results. There are, however, no statistically significant estimates in the table. Therefore, the observed reduction in accident severity cannot be attributed to a specific class of drivers' avoidance behavior. As a result, our findings are not primarily driven by avoidance behavior.

6. Conclusion

This paper studies how air pollution can affect road safety in terms of accident numbers and accident severity. By analyzing unique car insurance claim data provided by an auto insurance company in China, we can match the accidents with district-day air quality data calculated by IDW and investigate how the effects vary. We find that a 1 $\mu g/m^3$ increase in the PM2.5 leads to a 0.12 % increase in the probability of claims and a 0.40 % increase in the number of claims within one day. However, we see a significant negative effect of air pollution on the average claim ratio and average insurance claim amount. An additional 1 $\mu g/m^3$ in the average concentration of PM2.5 leads to a 0.01 % decrease in the average claim ratio (equivalent to 1.20 % of the indicator average) and a 26.23 yuan decrease in the average claim amount. Considering the combined effect on both the number of claims and their average amount, for each 1 $\mu g/m^3$ increase in daily PM2.5, the district's daily total claim amount decreases by approximately 33.54 yuan. It is possible that on polluted days, the increase in traffic accidents is not caused deliberately by drivers and that people tend to be more cautious and protective to avoid these non-subjective behavioral biases.

Several studies have examined the effects of air pollution on road safety. Sager (2019) finds that increased air pollution results in more traffic accidents. In addition, Shr et al. (2023) indicate that air pollution affects drivers in two contrasting ways: it impairs their physiological and cognitive functions, which increases their accident risk, while it also heightens their risk aversion, which reduces accidents. Air pollution can decrease the number of accidents when its effects on reducing accidents through increased risk aversion outweigh its effects on increasing accidents through impaired physiological function. Our research provides additional evidence from a new perspective. We find that air pollution has opposing effects on accident numbers and severity due to its effects on cognitive ability and risk preference. Cognitive impairment contributes more to the increase in accident numbers, while heightened risk aversion contributes more to the reduction in accident severity. The opposing effects of cognition and risk attitudes allow us to observe their effects directly. When combining these opposing effects, we conclude that air pollution does not necessarily compromise road safety as long as drivers maintain sufficient caution to counteract impaired cognition.

The findings in this paper have important implications for environmental policy evaluations. Although they do not take the place of effective policies to reduce air pollution, which remain essential, environmental policies educating individuals to mitigate their exposure to air pollution's adverse effects are important. For instance, from the perspective of road safety, driving cautiously and taking precautions can effectively reduce the severity of car accidents caused by air pollution. Policymakers may need to provide the public with more information on how air pollution can influence road safety. This will help raise public awareness of accidents caused by air pollution and provide policymakers and the public with methods of reducing such accidents.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chieco.2024.102261.

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