Air Pollution and Economic Activity: Evidence from Foot Traffic Patterns*

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Abstract

I investigate how air pollution affects economic activity. Using over 37 billion phone-location-based foot traffic data points from SafeGraph, I conduct a large-scale analysis to examine the causal effect of air pollution on activity patterns across the US. Using changes in local wind direction as an instrument for air pollution, I characterize the dynamic response to pollution exposure. I find that PM2.5 reduces economic activity in both the short and medium run, with effects persisting for up to two weeks before partially recovering. The reductions are widespread across different economic sectors, with recreational activities experiencing the largest decline. The effect is more pronounced in higher-income counties and areas with larger shares of children, suggesting greater awareness among wealthier or more vulnerable populations.

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1 Introduction

Air pollution imposes significant costs on human well-being. Its negative impacts on morbidity and mortality are well-documented (Currie and Neidell, 2005; He et al., 2016; Deschenes et al., 2017; Deryugina et al., 2019; Molitor et al., 2023; Barwick et al., 2024). Air pollution can also influence daily behaviors, affecting decisions about where people go and what they do. However, the extent to which air pollution affects economic activities remains largely unexplored. Prior studies typically focus on specific types of activities, such as visits to zoos, national parks, or movie theaters (Neidell, 2009; Keiser et al., 2018; He et al., 2022). Yet, air pollution may have much broader effects, affecting other economically important activities such as shopping and restaurant dining.[1] Widespread behavioral changes can carry significant economic implications, as reductions in economic activity due to air pollution can lower overall economic output. Quantifying these broader effects of air pollution on daily activities is important for understanding its impact on human welfare and for designing optimal environmental policies.

In this paper, I conduct the first large-scale estimation of the causal effect of daily air pollution fluctuations on economic activity in the United States. Conventional datasets on daily activities often focus on specific regions or sectors (e.g., hiking, cycling, or zoo visits), making it difficult to assess the broader effects of air pollution on economic activities. I address this issue using foot traffic data from SafeGraph, which aggregates de-identified geospatial data from millions of US smartphones. My dataset combines over 37 billion trips across a broad range of industries with satellite-based air pollution data covering the continental United States from 2018 to 2021. A primary identification concern when estimating the effect of air pollution is endogeneity. For instance, Ordinary Least Squares (OLS) estimates may be biased due to reverse causality, as visitation-related traffic could increase local air pollution. To address this concern, I use changes in wind direction as an instrumental variable (IV) for air pollution to estimate its causal effect on daily economic activities.

I find that air pollution leads to statistically and economically significant reductions in daily activities. On average, a 1 $\mu g/m^3$ increase in PM2.5 concentration—approximately 10% of the sample mean—results in a 0.29% decrease in daily activity in the short run (contemporaneous), which corresponds to a nationwide

[1] In my sample, retail trade, accommodation and food services, and entertainment sectors are the three largest sectors, accounting for more than 60% of trips.

reduction of 24.5 million trips annually.[2] In the medium run (over one month), the cumulative effect of a one-day air pollution exposure deepens over two weeks, reaching a 1.27% decline, before gradually recovering. By the end of one month, the point estimate is about two times larger than the contemporaneous effect. However, as the time window extends, the estimates become less precise due to wider standard errors. This pattern of persistent decline followed by partial recovery may reflect temporary health impacts of pollution, which take time to recover and still suppress activity even after air quality improves.

The reductions are significant across many industries, indicating that the effect of air pollution on daily activities is more widespread than previously thought. Entertainment and recreation activities experience the most substantial declines (a 1 $\mu g/m^3$ increase in PM2.5 concentration results in a 0.47% contemporaneous decrease in recreational activities), likely due to the greater flexibility of these activities compared to other daily routines. Reductions are also more pronounced for outdoor facilities than for indoor ones, presumably because outdoor activities amplify the negative health effects of pollution through increased respiration and exposure.

I also examine heterogeneity in responses to air pollution across different income levels and demographic groups. The reduction in daily activities is more pronounced in counties with higher incomes and larger proportions of children, suggesting that wealthier or more vulnerable populations may have greater awareness of elevated air pollution levels. I find that minority populations exhibit smaller behavioral responses to air pollution, which may partially explain disproportionately greater negative health impacts of air pollution on Black individuals compared to White individuals (Alexander and Currie, 2017; Gillingham and Huang, 2021). While previous literature on environmental injustice has primarily focused on the unequal distribution of pollution (Banzhaf et al., 2019; Jbaily et al., 2022), my findings emphasize the role of avoidance behavior in exacerbating these disparities. Even when exposed to the same levels of air pollution, low-income and minority groups are less likely to adjust their behavior to mitigate exposure, which may further deepen environmental justice issues. Given that these groups are disproportionately likely to live in more polluted areas (Mikati et al., 2018; Heblich et al., 2021; Tessum et al., 2021), addressing this unequal burden may require targeted policy interventions.

This paper makes three main contributions. First, it provides the first large-

[2] This is calculated as 0.29% $\times$ 0.06985 visits per person per day $\times$ 331.9 million people $\times$ 365 days $\approx$ 24.6 million trips annually.

scale estimation of the causal effect of air pollution on daily activities in the United States. Existing literature studying the effects of air pollution on daily activities generally relies on limited samples from specific regions (Bresnahan et al., 1997; Zivin and Neidell, 2009), or a specific activity type, such as visitin national parks (Keiser et al., 2018), camping (Gellman et al., 2022) or watching movies (He et al., 2022), which makes the generalizability of these estimates unclear. In contrast, my analysis uses nationwide phone-location data and examines a broader range of activities, making it more representative than previous studies. My findings suggest that air pollution leads to reductions in activities across most industries, indicating that the behavioral response to air pollution is more widespread than previously understood.

Second, this paper investigates whether individuals respond to day-to-day pollution fluctuations, adding to the relatively understudied topic of avoidance behavior. Previous studies show that air quality alerts prompt avoidance behavior (Neidell, 2009; Altindag et al., 2017). However, air quality warnings are rare and triggered only when the Air Quality Index exceeds a certain level, while negative effects of air pollution increase even before this threshold (Zivin and Neidell, 2009). Therefore, how individuals respond to these alerts does not necessarily reflect how they respond to air quality itself. In the absence of an air quality alert, individuals might not be aware of elevated pollution levels. My results are not solely driven by air quality alerts, indicating that people adjust their activities in response to more common, everyday pollution fluctuations. This finding suggests that avoidance behavior is more widespread than previously recognized, which in turn implies that the costs of pollution are underestimated.

Third, this paper highlights the importance of characterizing behavioral responses when quantifying the externalities of air pollution. Such responses can be either proactive, based on information or perceived risk, or reactive, driven by health symptoms. Ignoring these changes biases estimates downward, since health impacts would be larger if people continued their usual activities despite pollution. At the same time, behavioral adjustments impose their own costs, either through additional expenditures (Ito and Zhang, 2020; Zhang and Mu, 2018) or foregone utility. For example, staying home and limiting daily activities may reduce physical activity, increasing risks of obesity (Hankinson et al., 2010), depression, and anxiety (Paluska and Schwenk, 2000), which in turn generate broader societal costs. Shifts in behavior can also disrupt key industries and lower overall economic output. Because these responses are widespread, accurately quantifying them is essential for understanding the true costs of air pollution and designing effective policies.

The rest of the paper is organized as follows. Section 2 describes the data and provides summary statistics. Section 3 presents the conceptual framework. Section 4 introduces the empirical strategy. Section 5 presents the main results, examines heterogeneity, explores mechanisms, and conducts a welfare analysis. Section 6 reports robustness checks. Section 7 concludes.

2 Data

The data used in the paper comes from three main sources: mobile phone-based economic activity data from SafeGraph, satellite-based air pollution from the Copernicus Atmosphere Monitoring Service global reanalysis (EAC4), and satellite-based weather data from EAC4 and European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA5). The linkages and further details are described below.

2.1 Economic Activity Data

I obtain the economic activity data from SafeGraph.[3] The dataset includes information collected from over 45 million smart mobile devices and covers over 3.6 million Points of Interest (POI) across the United States. In total, I obtain over 37 billion trips from January 1, 2018, to December 30, 2021, across the United States. As shown in Table C.1, the vast majority of trips documented in the SafeGraph data are business-related, including visits to retail stores, hotels, restaurants, and entertainment facilities, which account for 57% of the total raw visits.

SafeGraph conducts a data quality evaluation by comparing its demographic data with the American Community Survey (ACS) data from the US Census and finds that its data are statistically representative of the population at the county level and above (Squire, 2019; Chang et al., 2022). Therefore, for empirical analysis, I match each location to its county based on latitude and longitude, and then aggregate visits to the county level. After aggregating all visits to the county level, I have 4,507,400 county-day observations. Additionally, since the dataset includes industry categories based on the North American Industry Classification System (NAICS) code, I am able to analyze foot traffic to different categories separately. The number of county-

[3] https://www.safegraph.com/. Accessed Sep 12, 2023.

day observations for each category is shown in Table 1.[4]

Because this dataset does not contain socioeconomic or demographic information about mobile device users for privacy reasons, I obtain county-level population and income data from the United States Census Bureau. Since county populations vary widely and more populated counties tend to have more visits, I use visit rates rather than raw visit numbers as the dependent variable. To calculate county-level visit rates, I aggregate the total number of visits in each county and then divide by the county's total population.

2.2 Air Pollution Data

The Environmental Protection Agency (EPA) pollution monitors provide valuable air quality data, but coverage is limited: more than half of the monitors only collect data on a 1-in-3-day or 1-in-6-day schedule, resulting in a lack of data on certain days.[5] Interpolating the missing data on these days can lead to bias, as air quality on unmonitored days tends to be worse than on monitored days due to strategic responses (Zou, 2021).

Therefore, rather than using monitor-based data, I use satellite-based air pollution data from the EAC4 reanalysis database.[6] EAC4 reports PM2.5 and other atmospheric data every 3 hours on a $0.75° \times 0.75°$ grid ($\approx 81\,km \times 81\,km$), which is derived from a combination of satellite observations and atmospheric model simulations. I construct county-level daily PM2.5 in the following way: for counties covered by multiple grid points, I average the gridded values overlapping each county; for counties without grid points, I interpolate their PM2.5 levels using inverse distance weighting (IDW) based on the latitude and longitude of the county centroid. I then match the visit data with the air pollution data using county code and date. Figure C.1 shows the average county-level visit rates and PM2.5 levels from January 1, 2018, to December 30, 2021. As a few counties do not have any visit data from SafeGraph, there are some missing values in the figure.

[4]Note that the number of observations varies across categories because some counties may not have facilities of certain types.

[5]See EPA's Sampling Schedule Calendar: https://www.epa.gov/amtic/sampling-schedule-calendar

[6]See https://ads.atmosphere.copernicus.eu/cdsapp#!/dataset/cams-global-reanalysis-eac4?tab=overview. Accessed September 19, 2022.

2.3 Weather Data

The analysis in this paper contains a flexible set of control variables for weather, including temperature, wind speed, dew point, and precipitation. Additionally, wind direction is used as the instrument for PM2.5 concentrations.

Daily temperature, wind direction, wind speed, and dew point data are also obtained from the EAC4 reanalysis database. I average the daily measures across all grid points in a particular county to obtain the county-level daily measure. For counties without grid points, I interpolate their temperature, wind direction, wind speed, and dew point using IDW based on the latitude and longitude of the county centroid. Specifically, wind directions and wind speeds are constructed using the East-West wind vector (u-wind) and the North-South wind vector (v-wind) provided in the database.[7] Wind direction is defined as the direction the wind is blowing from.

In addition, I obtain precipitation data from the Copernicus ERA5 hourly reanalysis database. Precipitation data are reported on a $0.25° \times 0.25°$ grid ($\approx 27km \times 27km$). I construct the county-level daily precipitation by averaging the hourly data on a given day with grid points within a particular county. For counties without grid points, I interpolate their precipitation using IDW based on the latitude and longitude of the county centroid.

2.4 Summary Statistics

Table 1 displays summary statistics for the main estimation sample, consisting of 4,507,400 county-day observations. The average daily concentration of PM2.5 is 11.5 $\mu g/m^3$, with a standard deviation of 16.64.[8] Demographic characteristics are measured at the county level in 2017. On average, counties in the sample have a population of approximately 105,050, with about 5.8% of residents under age 5, 77% of residents White, and a per capita income of roughly $26,000.

The average daily visit rate across all POIs within counties is 69.85 visits per 1,000 people.[9] The Retail Trade sector exhibits the highest mean visit rate at 22.50

[7] Note that wind directions and speed are vectors, so they cannot be averaged or interpolated numerically. Therefore, when averaging or interpolating, I first take the average of the two vectors and then calculate the average wind direction and wind speed using the average vectors.

[8] This is slightly higher than the average PM2.5 concentration calculated using EPA ground monitors. One possible explanation for this discrepancy is strategic monitor placement, as discussed in Grainger et al. (2019).

[9] Note that the data from SafeGraph were collected from over 45 million mobile devices, roughly 14% of the US population. The raw number of visits before aggregating to the county level is reported in Table C.1.

per 1,000 people, followed by the Accommodation and Food Services sector at 14.58 visits per 1,000 people. Most counties have at least some activity in each sector; a notable exception is the Mining, Quarrying, and Oil and Gas Extraction sector, where relevant POIs are missing in the majority of counties, resulting in very few observations.

Table 1. Summary statistics

Variables	Mean	SD	N
Pollution			
PM2.5 ($\mu g/m^3$)	11.50	16.64	4,507,400
Weather			
Temperature (°C)	13.53	10.73	4,507,400
Total precipitation (mm)	0.31	0.70	4,507,400
Wind direction (°)	193.19	94.75	4,507,400
Wind speed (m/s)	2.73	1.55	4,507,400
Dew point (°C)	6.81	10.81	4,507,400
Visibility (km)	17.55	3.87	4,507,400
Demographics			
Population	105,050	336,591	3,100
Age under 5 (%)	5.84	1.19	3,100
White (non-Hispanic) (%)	77.13	19.77	3,100
Per capita income (USD)	26,011	6,215	3,100
Visit Rates (per 1,000 people)			
All POIs	69.85	41.51	4,507,400
44-45: Retail Trade	22.50	14.28	4,506,558
72: Accommodation and Food Services	14.58	12.39	4,491,452
61: Educational Services	8.03	8.84	4,466,749
71: Arts, Entertainment, and Recreation	6.48	9.13	4,322,150
53: Real Estate and Rental and Leasing	5.73	7.44	3,858,106
62: Health Care and Social Assistance	4.88	3.86	4,449,158
81: Other Services	4.54	6.01	4,495,995
48-49: Transportation and Warehousing	1.33	2.62	4,482,408
92: Public Administration	1.11	1.55	4,468,576
31-33: Manufacturing	0.87	2.43	3,875,683
52: Finance and Insurance	0.73	0.72	4,282,607
51: Information	0.46	0.78	3,944,703
42: Wholesale Trade	0.45	0.76	3,677,317
54: Professional, Scientific, and Technical Services	0.41	0.48	4,040,757
23: Construction	0.31	0.50	3,614,912
55: Management of Companies and Enterprises	0.31	1.70	1,383,221
22: Utilities	0.24	0.63	2,228,604
56: Administrative and Support and Waste Services	0.18	0.34	3,009,650
21: Mining, Quarrying, and Oil and Gas Extraction	0.17	0.20	8,750
11: Agriculture, Forestry, Fishing and Hunting	0.11	0.27	658,854

Notes: Demographic variables are measured at the county level as of 2017.

3 Conceptual Framework

To motivate the empirical analysis, I consider a simple dynamic setting in which individuals choose daily activity a_t at time t to balance the enjoyment of activity against the health costs of pollution exposure. Per-period utility is given by:

$$U_t \;=\; u(a_t, h_t) \;-\; r_t\,\delta(a_t),$$

where a_t is activity level, h_t denotes an individual's health condition, and r_t is ambient pollution at time t. I assume $u_a(a_t, h_t) > 0$, $u_{aa}(a_t, h_t) < 0$, and $u_h(a_t, h_t) > 0$, reflecting diminishing marginal utility of activity and positive marginal utility of health. $\delta(a_t)$ captures the contemporaneous utility cost of activity under pollution. This cost may arise from immediate discomfort due to exposure, or from concerns about perceived pollution risk. I assume $\delta'(a_t) > 0$, meaning that more activity increases exposure cost, and $\delta''(a_t) \geq 0$, meaning the marginal cost of additional activity is non-decreasing.

Health evolves according to partial adjustment:

$$h_{t+1} = h_t + \rho(\bar{h} - h_t) - \theta(r_t)\,a_t, \tag{1}$$

where $\rho \in (0, 1)$ is the recovery rate toward baseline health $\bar{h}$, and $\theta(r_t)$ is the pollution-induced damage per unit of activity. I assume $\theta'(r_t) \geq 0$, implying the marginal harm from an extra unit of activity is non-decreasing (Xia et al., 2022; Colmer et al., 2021).

The parameter $\bar{h}$ represents an individual's baseline health capacity—shaped by factors such as age, chronic conditions, or other long-term endowments—that determines how much utility they derive from activity and how resilient they are to pollution exposure. Over the life cycle, $\bar{h}$ would decline as individuals age or accumulate health shocks, but over the one-month window of interest it can be treated as stable. The adjustment term $\rho(\bar{h} - h_t)$ reflects natural recovery of health toward this baseline, while the term $\theta(r_t)a_t$ captures short-run loss of health from engaging in activity under pollution exposure.

The individual solves the intertemporal problem:

$$\max_{\{a_t\}_{t=0}^{T}} \sum_{t=0}^{T} \beta^t \left[u(a_t, h_t) - r_t\,\delta(a_t)\right] \quad \text{s.t.} \quad h_{t+1} = h_t + \rho(\bar{h} - h_t) - \theta(r_t)\,a_t,$$

where $\beta \in (0, 1]$ is the intertemporal discount factor. The Lagrangian is:

$$\mathcal{L} = \sum_{t=0}^{T} \beta^t \left[u(a_t, h_t) - r_t\, \delta(a_t)\right] + \sum_{t=0}^{T} \beta^{t+1} m_{t+1} \left[h_t + \rho(\bar{h} - h_t) - \theta(r_t)\, a_t - h_{t+1}\right],$$

where m_t is the shadow value of health at the start of period t. The first-order condition (FOC) with respect to a_t is:

$$u_a(a_t, h_t) - r_t\, \delta'(a_t) - \beta\, \theta(r_t)\, m_{t+1} = 0, \tag{2}$$

and m_t evolves as:

$$m_t = u_h(a_t, h_t) + \beta(1 - \rho)\, m_{t+1}. \tag{3}$$

Intuitively, in Equation (2), the marginal enjoyment of activity today $u_a(a_t, h_t)$ equals its marginal costs: the marginal disutility today $r_t\delta'(a_t)$ and the discounted shadow cost of tomorrow's health loss $\beta\, \theta(r_t) m_{t+1}$. Equation (3) defines the shadow value of health: one extra unit of health at the start of day t is worth its direct marginal utility today, $u_h(a_t, h_t)$, plus the discounted continuation value that carries forward at rate $1 - \rho$.

Prediction 1 (Same-day avoidance). Define

$$F(a_t; r_t, m_{t+1}, h_t) \equiv u_a(a_t, h_t) - r_t\, \delta'(a_t) - \beta\, \theta(r_t)\, m_{t+1} = 0.$$

Applying the implicit function theorem,

$$\frac{\partial a_t^*}{\partial r_t} = -\frac{F_r}{F_a} = \frac{\delta'(a_t) + \beta\, \theta'(r_t)\, m_{t+1}}{u_{aa}(a_t, h_t) - r_t\, \delta''(a_t)}.$$

The denominator is negative by concavity of utility in activity ($u_{aa} < 0$) and convexity of the exposure cost ($\delta'' \geq 0$, ensuring an interior solution). The numerator is positive since $\delta'(a_t) > 0$ and $\theta'(r_t) \geq 0$, with $m_{t+1} > 0$. Hence,

$$\frac{\partial a_t^*}{\partial r_t} < 0.$$

Intuitively, higher pollution increases both the direct disutility of engaging in activity ($r_t\delta'(a_t)$) and the future health cost of today's activity ($\beta\theta(r_t)m_{t+1}$). Together, these effects dominate the marginal benefit of activity, leading individuals to optimally reduce activity on polluted days.

Prediction 2 (Persistence and rebound). From Equation (1),

$$\frac{\partial h_{t+1}}{\partial r_t} = -\,\theta'(r_t)\,a_t \;-\; \theta(r_t)\,\frac{\partial a_t^*}{\partial r_t}.$$

The first term is negative since $\theta'(r_t) \geq 0$. The second term is positive since $\theta(r_t) > 0$ and $\partial a_t^*/\partial r_t < 0$; this captures the offsetting effect of behavioral responses, as individuals reduce activity when air quality worsens. The overall effect is negative whenever

$$\theta'(r_t)a_t \;>\; -\,\theta(r_t)\,\frac{\partial a_t^*}{\partial r_t},$$

meaning that the increase in per-unit health damage caused by higher pollution dominates the health savings from reduced activity. This condition is reasonable: although individuals adjust their behavior, these responses are generally modest compared to the physiological damage caused by particulate pollution, and people cannot eliminate activity altogether because of daily needs. Thus, in practice, pollution still worsens next-day health even after accounting for these responses.

A decline in h_{t+1} raises the shadow value m_{t+1} by Equation (3). If $u_{ah}(a,h) \geq 0$ (activity and health are complements), then better health makes activity more enjoyable. In this case, a decline in health raises the marginal value of health and feeds back into the FOC at $t+1$, keeping activity suppressed even once pollution returns to normal levels. By contrast, if $u_{ah}(a,h) < 0$ (activity and health are substitutes), then the mechanism weakens: a decline in health would not reinforce avoidance, and activity may rebound more quickly or even overshoot. Iterating Equation (1) yields

$$h_{t+k} - \bar{h} = (1-\rho)^k(h_t - \bar{h}) - \sum_{j=0}^{k-1}(1-\rho)^{k-1-j}\theta(r_{t+j})\,a_{t+j},$$

so health converges toward $\bar{h}$ at rate ρ when pollution normalizes. Taken together, if marginal harm is non-decreasing in pollution and activity and health are complements, a pollution shock reduces health today, raises the shadow value of health tomorrow, and keeps activity suppressed in the near term before it gradually recovers as the health stock heals. This mechanism implies that whether we observe persistence in activity responses is informative about the complementarity between health and activity, a hypothesis I return to in the empirical analysis.

Prediction 3 (Heterogeneity). To capture heterogeneity in behavioral responses, let a socioeconomic or demographic characteristic y (such as income or race) scale the contemporaneous exposure cost via $\lambda(y)$ with $\lambda'(y) > 0$. Rewrite the FOC as

$$F(a_t; r_t, m_{t+1}, h_t, y) \;\equiv\; u_a(a_t, h_t) \;-\; \lambda(y)\, r_t\, \delta'(a_t) \;-\; \beta\, \theta(r_t)\, m_{t+1} \;=\; 0.$$

Differentiating $F(\cdot) = 0$ w.r.t. y and applying the implicit function theorem,

$$\frac{\partial a_t^*}{\partial y} = \frac{\lambda'(y)\, r_t\, \delta'(a_t)}{u_{aa}(a_t, h_t) - \lambda(y)\, r_t\, \delta''(a_t)} < 0,$$

since $\lambda'(y) > 0$, $\delta'(a_t) > 0$, $r_t \geq 0$, and the denominator is negative (interior solution). In other words, groups with higher y place a larger weight on exposure costs (bigger λ), so they optimally reduce activity levels on polluted days. This channel captures the stronger avoidance observed among higher-income groups and among whites.

Similarly, let biological or demographic vulnerability z (e.g., share of children) shift the per-unit damage of activity through $\theta = \theta(r_t; z)$ with $\theta_z(r_t; z) > 0$. Differentiating $F(\cdot) = 0$ w.r.t. z,

$$\frac{\partial a_t^*}{\partial z} = \frac{\beta\, \theta_z(r_t; z)\, m_{t+1}}{u_{aa}(a_t, h_t) - \lambda(y)\, r_t\, \delta''(a_t)} < 0,$$

since $\theta_z > 0$, $m_{t+1} > 0$, and the denominator is negative (interior solution). Hence biologically more vulnerable groups (higher z), such as populations with a higher share of children, optimally reduce activity more when pollution is high.

4 Empirical Strategy

My objective is to estimate the causal effect of acute (1-day) air pollution exposure on economic activity. Following Deryugina et al. (2019), I model this relationship as:

$$\frac{Y_{ct}^k}{Pop_c} = \beta^k \cdot PM2.5_{ct} + \mathbf{X}_{ct}^{k'}\gamma + \sigma_{cy} + \eta_{cm} + \mu_w + \psi_{my} + \epsilon_{ct} \tag{4}$$

where c indexes counties, t indexes time at the daily level, y indexes years, and m indexes months. The outcome variable, Y_{ct}^{k}, represents the cumulative visit rate in county c over the k days following exposure on day t (including same-day visits). Visit rates are calculated as the total number of visits to all facilities in county c on date t, divided by the county's 2020 population.[10] The parameter of interest, β^k, captures the effect of acute PM2.5 exposure on k-day economic activity. To ensure that β^k is not capturing the effect of weather conditions during the outcome window, the specification includes contemporaneous and k-lead values of the weather variables. I also include two lags of the weather controls to address potential confounding from past weather conditions. To minimize concerns about autocorrelation, my OLS estimates control for two leads and two lags of PM2.5, while my IV estimates control for two leads and two lags of the instruments.

My main specification controls for daily temperature, precipitation, wind speed, and dew point. I generate indicators for daily average temperatures falling into one of 14 bins, ranging from –9 to –6°C up to 24 to 27°C, with additional bins for temperatures below –9°C and above 27°C. I also generate indicators for precipitation quartiles, wind speed quintiles, and dew point quintiles.[11] I then generate a set of indicators for all possible interactions of these weather variables and include them in my regressions as $\mathbf{X}_{ct}^{k}$. My estimates are robust to using less flexible weather controls or omitting weather controls entirely (Table 4). These results reinforce the assumption that my estimates are not driven by unobserved climatic factors that are correlated with both wind direction and economic activity.

In addition, I include a rich set of fixed effects, including county-by-year fixed effects σ_{cy}, county-by-month fixed effects η_{cm}, month-by-year fixed effects ψ_{my} and day-of-week fixed effects μ_w. Specifically, county-by-year fixed effects σ_{cy} pick up within-year variations in county-level factors that determine visits but are not captured by the control variables, such as demographic characteristics and economic conditions. County-by-month fixed effects η_{cm} control for seasonal unobservables across counties, such as different peak seasons due to different geographic features. Day-of-week fixed effects μ_w pick up cyclical visit patterns within the week. Lastly, month-by-year fixed effects ψ_{my} captures the time-varying shocks that are common in each month, such as economic recessions and pandemic outbreaks. I also examine the robustness of the results by including different fixed effects. The standard errors

[10] I use 2020 Census counts because they provide more accurate benchmarks than ACS intercensal estimates.

[11] Precipitation is categorized into quartiles instead of quintiles due to a high number of zero observations.

are clustered at the county level.

For OLS estimates of Equation (4) to be unbiased, the identifying assumption is that, conditional on control variables and fixed effects, unobserved determinants of visit rates (ϵ_{ct}) are uncorrelated with variation in PM2.5. Although high-frequency air pollution tends to be more random than long-term trends, some sources of endogeneity may still bias the estimate of β^k. First, there may be omitted variables that affect both ambient pollution and economic activity. For example, a local event could increase PM2.5 levels by raising traffic while simultaneously influencing individuals' time allocation. Second, although reverse causality is likely minimal, it cannot be entirely ruled out. If people choose to stay home rather than go out, the resulting decline in economic activity could also reduce local emissions. Finally, measurement error is a concern: satellite-based county averages are noisy proxies for actual exposure, as spatial aggregation and interpolation smooth out local variation and can lead to attenuation bias.

To address this concern, I leverage the pollution variation due to changes in wind patterns to identify pollution impacts. Specifically, since wind directions are random, I use the changes in wind direction as an instrumental variable for air pollution to derive the causal relationship (Deryugina et al., 2019). The assumption of this approach is that, after controlling for covariates and fixed effects, changes in wind direction only affect people's economic activity through their effects on air pollution. The specification for the first stage is:

$$PM2.5_{ct} = \sum_{g \in G} \sum_{b=0}^{3} \pi_b^g \mathbf{1}[G_c = g] \cdot WindDir_{ct}^{90b} + \mathbf{X}_{ct}\gamma + \sigma_{cy} + \eta_{cm} + \mu_w + \psi_{my} + \epsilon_{ct} \quad (5)$$

In Equation (5), the instrumental variable is constructed in the following manner. $WindDir_{ct}^{90b}$ equals 1 if wind direction in county c falls in the 90-degree interval [90b, 90b+90) and 0 otherwise. Because the relationship between wind direction and pollution transport is location-specific, I allow the effect of each wind instrument on PM2.5, denoted by π_b^g, to vary across geographic regions.[12] To define these regions, I apply the K-means clustering algorithm to county centroids (latitude and longitude), classifying counties into 20 spatial groups. The clustering result is shown in Figure C.2. $\mathbf{1}[G_c = g]$ equals 1 if county c is classified into monitor group g and 0 otherwise.

[12]Because the effect of wind direction on pollution depends on the surrounding geography, a westerly wind blowing clean ocean air into California is likely to have a very different impact on local pollution levels than a westerly wind carrying industrial emissions into a community located just east of Houston.

Other control variables X_{ct} and fixed effects are defined as in Equation (4).

Air pollution in a given location can originate from sources that are either close by or far away. For instance, a city's air quality may be affected by nearby traffic emissions, as well as by smoke from wildfires or pollutants released by power plants located hundreds of miles away. The source location matters because emissions from local sources tend to disperse unevenly across nearby areas, while emissions from more distant sources disperse more uniformly across the same region.

Equation (5) allows the effect of wind direction on air pollution to vary across geographic groups but not within a group. Intuitively, non-local sources located outside of the cluster are more likely to have similar effects on pollution levels in all (or most) counties in the cluster group. As a result, Equation (5) is more likely to capture variation in pollution driven by non-local sources. This is advantageous because pollution driven by local sources may not affect all individuals residing within the area in the same way, leading to measurement error.[13] In Section 6, I provide evidence that the pollution variation exploited in my design is primarily driven by non-local sources. Therefore, the effects of wind direction on pollution should be similar for all counties within the same geographic cluster. I employ 4 bins and 20 clusters for computational ease, and the results are robust to varying the number of wind direction bins and geographic clusters (Table C.10). Figure C.3 illustrates my first-stage variation using California state as an example.

5 Empirical Results

5.1 Impact of Pollution on Economic Activity

I begin by estimating the effect of daily air pollution exposure on same-day activity, i.e., $k = 0$ in Equation (4). Table 2 displays estimates from both OLS and IV models. For the IV strategy, I use daily changes in county-level wind direction as an instrument for daily changes in county-level PM2.5 concentrations. The first-stage F-statistic in column (2) is 87.36, which indicates that weak instrument concerns are minimal. Since PM2.5 is endogenous, I rely on the IV approach as the preferred empirical strategy. The estimate in column (2) implies that a 1 $\mu g/m^3$ increase in PM2.5 reduces visit rates by approximately 0.20 visits per thousand people, equiv-

[13] Consider a local pollution source located in the center of a cluster. When the wind blows from the west, counties to the west of this source will record low pollution levels, and counties to the east will record high pollution levels. In this case, the instrument does not generate consistent pollution variation across counties in the cluster, weakening the first stage.

alent to a 0.29% decline relative to the daily mean. columns (3)-(5) report the effects for the three largest sectors in the sample: retail trade, accommodation and food services, and entertainment and recreation. column (5) shows that the relative effect is largest in the entertainment and recreation sector, at about 0.47%, nearly twice the overall average. This result is potentially because recreational activities are more flexible and easier to adjust or cancel.

The IV estimate in column (2) is substantially larger than the OLS estimate in column (1), suggesting that OLS estimation suffers from significant bias. This downward bias is common in quasi-experimental studies on air pollution and is generally thought to be, at least in part, due to measurement errors in pollution exposure (Schlenker and Walker, 2016; Ebenstein et al., 2017; Deryugina et al., 2019; Alexander and Schwandt, 2022).

Table 2. OLS and IV estimates of the effect of PM2.5 on 1-day visits

	OLS	IV			
	(1)	(2)	(3)	(4)	(5)
PM2.5 ($\mu g/m^3$)	-0.003***	-0.20***	-0.06***	-0.04***	-0.03***
	(0.0014)	(0.01)	(0.005)	(0.005)	(0.003)
Relative effect (%)	-0.004	-0.29	-0.27	-0.28	-0.47
Location types	All	All	Retail Trade	Accommodation and Food Services	Entertainment and Recreation
First-stage F-statistic		87.36	87.26	81.88	82.18
Dependent variable mean	69.85	69.85	22.40	14.49	6.41
Fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.87	0.86	0.90	0.85	0.73
Observations	4,501,200	4,495,000	4,487,988	4,472,910	4,304,146

Notes: This table reports the OLS and IV estimates using Equation (4) and (5). The dependent variable is number of visits per thousand people on the day of exposure. All regressions control for bins of mean temperature, precipitation, wind speed, and dew point, as well as two lags of these weather controls. IV estimates also include two lags and two leads of instruments. Fixed effects include county-by-year, county-by-month, day-of-week, and month-by-year fixed effects. Column (1) and (2) show the effect for all POIs, whereas columns (3)-(5) are for three specific types of POIs. Standard errors are clustered at the county level. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Figure 1 extends this analysis by presenting percentage changes across all economic sectors.[14] While most estimates are negative, the magnitudes vary, ranging from 0.47% in entertainment and recreation to 0.08% in health care. I find no statistically significant effect for several non-consumer-facing sectors, including manufacturing, waste management, public administration, professional and technical

[14] Sectors are defined by 2-digit NAICS codes. The raw number of visits and each industry's share in the sample are reported in Table C.1.

services, wholesale trade, and construction. This suggests that sectors less reliant on consumer foot traffic are less sensitive to air pollution.

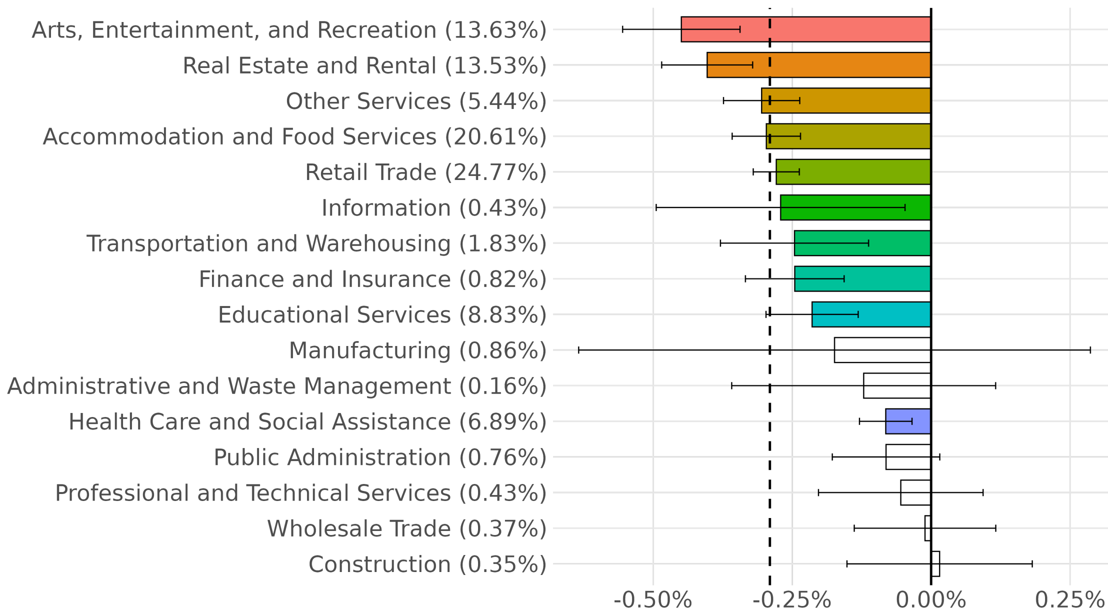


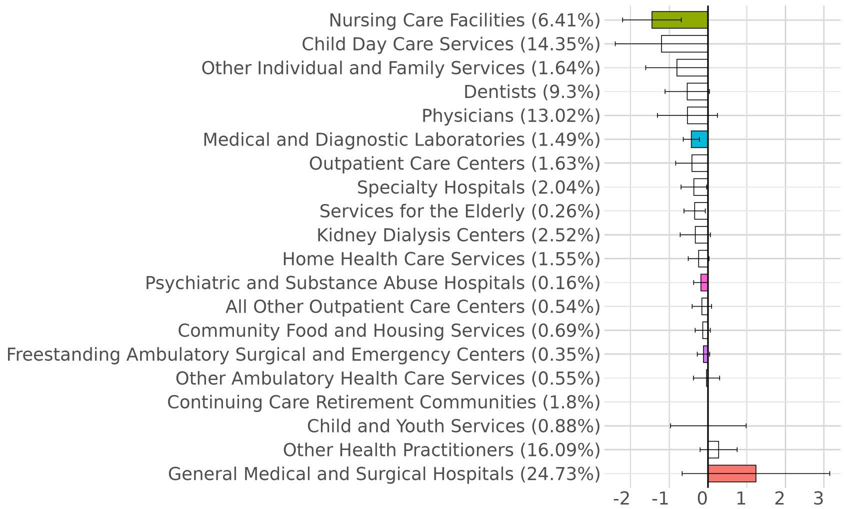
Figure 1. Relative effect (percent of 1-day visits) by 2-digit NAICS codes

Notes: This figure displays the heterogeneous treatment effects of air pollution on daily activities across industries, categorized by their 2-digit NAICS codes. Each bar represents an IV estimate from Equation (4) of the effect of 1-day PM2.5 exposure on same-day visits in each sector. The percentage next to each industry name indicates its share of raw visits in the sample. Bars show estimated effects, and horizontal lines indicate 95% confidence intervals. The vertical black dashed line shows the average effect from the main results across all POIs. Industries accounting for less than 0.2% of raw visits are omitted due to high variance. Sectors with statistically insignificant estimates are displayed as hollow (white) bars. The corresponding absolute effects (in visits per thousand) are presented in Figure C.5.

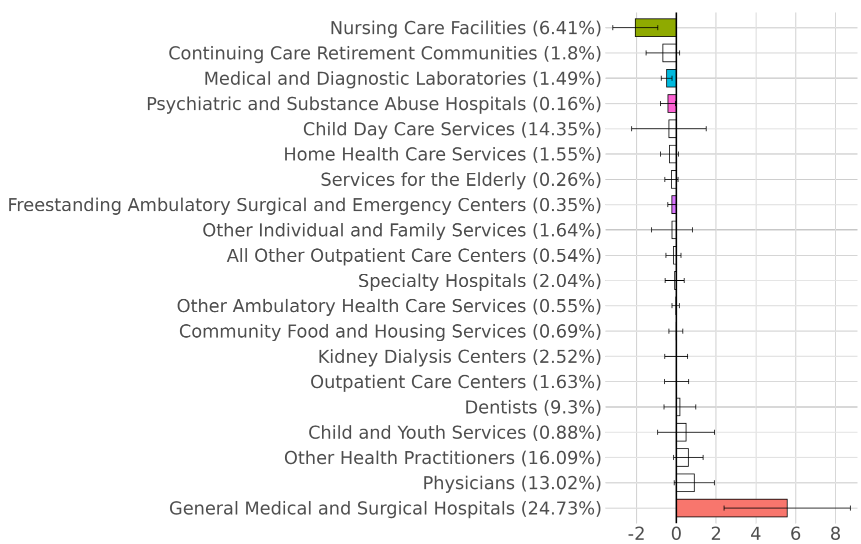
Prior studies find that air pollution increases hospital admissions (Schlenker and Walker, 2016; Deryugina et al., 2019; Ward, 2015; Wei et al., 2019; Gu et al., 2020; Dominici et al., 2006), but Figure 1 shows fewer visits in the broader NAICS "Health Care and Social Assistance" category. This is not necessarily a contradiction. Because NAICS does not provide a separate category for acute visits such as emergency, cardiovascular, or respiratory care, increases in these services can be masked by declines in routine visits, resulting in a net reduction. To probe this mechanism, I further disaggregate the health care sector into more detailed categories, distinguishing hospitals from a range of non-hospital services. As shown in Figure 2a, pollution reduces visits to several non-hospital services, including child day care and nursing care facilities. This pattern may reflect greater avoidance of non-urgent, in-person interactions on polluted days—for instance, keeping children home from day care or curbing nursing-home visitation. In contrast, general medical and surgical hospitals, which encompass emergency departments and provide cardiovascular and respiratory care, show an increase of about 1.24 visits per 1,000 people (0.07% relative to the mean) for a 1 $\mu g/m^3$ increase in PM2.5, although the estimate is imprecise.

If vulnerable populations are more likely to seek hospital care while others cut back on routine services, offsets should be smaller where the population is older (Schwartz, 1994). Consistent with this, in counties with an above-median elderly share, Figure 2b shows effects shifting from negative toward zero or positive, with a notable increase for general hospitals. Specifically, in above-median elderly counties, general hospitals show an increase of 5.6 visits per 1,000 people (0.33% relative to the mean) for a 1 $\mu g/m^3$ increase in PM2.5, and the effect is statistically significant. This suggests that pollution-induced demand for acute care is partly masked by concurrent reductions in other health care services.[15]

[15] For example, Liu et al. (2022) show that pollution increases the likelihood of refraining from health care visits in China.



(a) Absolute effect for all counties



(b) Absolute effect for high-elderly-share counties

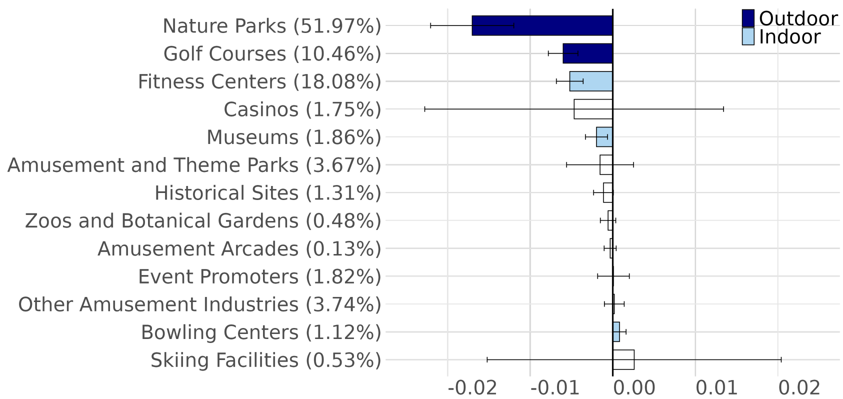
Figure 2. Heterogeneous effects of air pollution on visits to health care facilities

Notes: This figure displays the heterogeneous treatment effects of air pollution on visit rates to different health care facilities, defined by 6-digit NAICS codes. Panel (a) presents the absolute effect (visits per thousand) for all counties, while panel (b) shows the effect for counties where the elderly population share is above the median. Each bar shows an estimated effect; horizontal lines indicate 95% confidence intervals. Categories with statistically insignificant estimates are displayed as hollow (white) bars. Categories accounting for less than 0.1% of raw visits are omitted due to high variance.

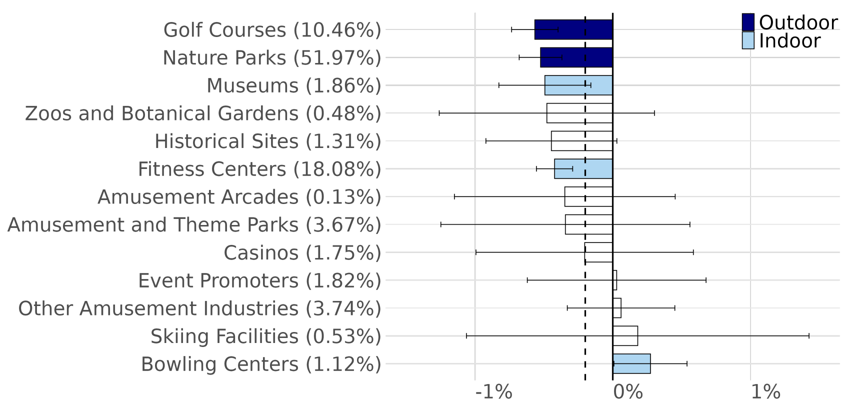
Next, I turn to entertainment and recreation—the most affected industry—and examine more detailed facility types.[16] As shown in Figure 3a, air pollution signifi-

[16]Facility shares are reported in Table C.3.

cantly reduces visits to nature parks, golf courses, fitness centers, and museums. In absolute terms, the declines range from 0.017 visits per thousand people for nature parks to 0.0002 visits per thousand for museums. When expressed in relative terms, however, the reductions are similar across facility types, at roughly 0.5% (Figure 3b). In contrast, visits to bowling centers increase slightly, by about 0.27%.



(a) Absolute effect (visits per thousand)



(b) Relative effect (% of day 0 visits)

Figure 3. Heterogeneous effects of air pollution on visits to recreational facilities

Notes: This figure displays the heterogeneous treatment effects of air pollution on visit rates at different recreational facilities, defined by 6-digit NAICS codes. Panel (a) shows the absolute effect in visits per thousand, and panel (b) presents the relative effect as a percentage of same-day visits. Outdoor facilities (darker blue) include golf courses and nature parks, while indoor facilities (lighter blue) include museums, fitness centers, and bowling centers. Each bar shows an estimated effect; horizontal lines indicate 95% confidence intervals. Categories with statistically insignificant estimates are displayed as hollow (white) bars. The vertical blue dashed line in panel (b) represents the average effect for all POIs. Categories accounting for less than 0.1% of raw visits are omitted due to high variance.

My estimates by sector are broadly consistent with prior studies (see Table C.2 for a summary of selected studies).[17] For recreation and entertainment, I find that a 1 $\mu g/m^3$ increase in PM2.5 (about a 10% change relative to the mean) reduces visits by 0.47%, consistent with evidence that pollution lowers outdoor exercise and park use. Fan (2024) estimate a 0.14% decline in outdoor activity per 1 $\mu g/m^3$ increase in PM2.5 in China, while Keiser et al. (2018) report that a 1 ppb rise in ozone decreases U.S. national park visits by 3.9% (about 1.8% for a 10% relative increase). For food services and retail trade, I find a 0.3% decline in visits from a 1 $\mu g/m^3$ increase in PM2.5, consistent with small but significant effects in Beijing: Sun et al. (2019) report declines of 0.15% for restaurants and 0.1% for shopping visits, while Gao et al. (2020) find a 0.65% decline in restaurant visits. For education, I estimate a 0.21% decline in visits, in line with studies showing that poor air quality disrupts learning environments. For example, Chen et al. (2000) find that a 10% increase in CO or O_3 raises school absence rates by about 1% in Nevada.

For health care, I estimate an overall 0.08% decline in visits per 1 $\mu g/m^3$ increase in PM2.5. While this may initially appear different from prior findings that pollution increases acute care visits, the patterns align once the sector is disaggregated. Deryugina et al. (2019) find that a 1 $\mu g/m^3$ increase in PM2.5 raises ER visits by 0.06% in the U.S., and Dardati et al. (2024) report increases of 0.03–0.07% in Chile. My results show that pollution reduces visits to non-hospital services such as nursing care and child day care, but general medical and surgical hospitals—which encompass emergency and respiratory care—show a positive effect (0.07%), of similar magnitude to prior work, though imprecise. Moreover, in counties with above-median elderly populations, hospital visits rise significantly by 0.33%, reinforcing that demand for acute care increases with pollution. Taken together, these results are consistent with prior evidence once one distinguishes between hospitals and other health care services, while also highlighting offsetting declines in routine care.

5.2 Dynamic Effects of Pollution on Economic Activity

Figure 4 presents IV estimates of the effect of a one-day, 1 $\mu g/m^3$ increase in PM2.5 on economic activity over the month following exposure. The estimate at day 0

[17] For comparability, I focus on studies that use pollution levels rather than alert thresholds, and I translate pollutants other than PM2.5 into percentage changes. Table C.2 reports the original units, as well as studies based on alerts.

corresponds to the estimate from column (2) of Table 2.[18] If the cumulative effect recovers over time, this suggests that people are making up for lost activity rather than forgoing it entirely. In contrast, if the cumulative effect continues to decrease, it suggests that pollution exposure imposes health costs that persist beyond the day of exposure, limiting individuals' ability to resume normal activities even after air quality improves. Another possibility is that temporary reductions in activity lead to behavioral inertia or habit formation, resulting in lower activity levels even after pollution conditions return to normal.

I find a continuous decline in economic activity lasting up to two weeks, from 0.29% on the first day to 1.27% after two weeks. Activity then gradually recovers, indicating that people partially make up for lost visits. By the end of one month, the cumulative decline is about twice as large as the contemporaneous decline, although estimates become less precise at longer horizons due to wider standard errors (Figure 4).[19] This dynamic aligns with findings from Barwick et al. (2024), who document that air pollution significantly reduces spending on necessities and supermarket visits in China within two weeks, followed by a recovery thereafter.

This observed pattern is consistent with mechanisms documented in previous literature. Acute air pollution exposure can trigger adverse health effects and cause people to feel unwell (Neidell et al., 2023; Schlenker and Walker, 2016; Deryugina et al., 2019), potentially reducing their willingness or ability to engage in regular economic activities (Graff Zivin and Neidell 2012; Hanna and Oliva 2015). Additionally, air pollution episodes have been shown to significantly increase household medical expenditures (Barwick et al., 2024), which could crowd out discretionary consumption. These combined health and economic impacts may explain the pronounced and persistent declines observed in discretionary sectors, such as recreation (Figure 5).

As a falsification test, Figure 4 also shows estimates of the effect of PM2.5 on cumulative activity in the two weeks *prior* to exposure. While there is some fluctuation, the pre-period estimates are small and show no clear trend, supporting the validity of my empirical strategy.

[18]Estimates are converted to percentage terms using average daily visit rates to ensure comparability with previous results.

[19]Appendix Figure C.6 extends the horizon to 100 days. The cumulative effect remains significantly below zero throughout this period, indicating that the decline does not fully disappear even in the longer run.

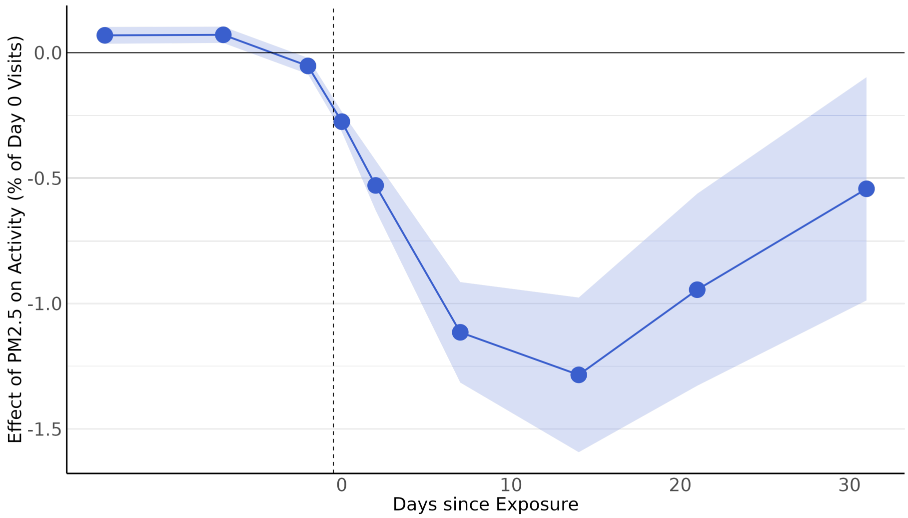


Figure 4. IV estimates of the effect of acute (1-day) PM2.5 on cumulative economic activity up to one month after exposure

Notes: This figure displays IV estimates of the effect of a 1-day, 1 $\mu g/m^3$ increase in PM2.5 on economic activity up to one month after exposure. Effects are expressed as a percentage of day 0 visits. Visit rates are measured as cumulative visits over windows ranging from 1 to 30 days, as indicated on the x-axis. Points show the estimates, vertical lines indicate 95% confidence intervals, and standard errors are clustered at the county level.

Figure 5 shows how the estimated cumulative effects of a one-day PM2.5 increase vary across economic sectors, focusing on the three largest sectors in my sample: retail trade, accommodation and food services, and arts, entertainment, and recreation. Consistent with the contemporaneous results, the recreation sector (green solid line) experiences the largest reduction, both immediate and persistent. Over one month, the cumulative effect in the recreation sector deepens, becoming roughly nine times larger than the contemporaneous impact. Retail trade (blue dashed line) and accommodation and food services (orange dashed line) exhibit similar magnitudes and trajectories. Although the cumulative effect in accommodation and food services shows a further decline over one month, it stabilizes after the first week, reflecting a persistent rather than worsening impact. Overall, these results indicate lasting negative effects of acute pollution exposure, strongest in the recreation sector and more moderate in retail trade and accommodation and food services.

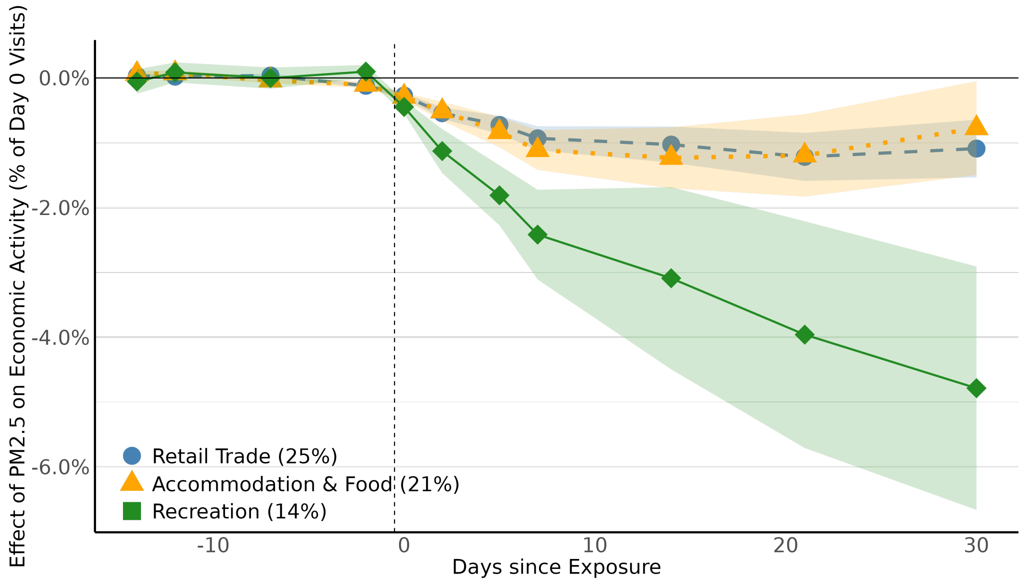


Figure 5. IV estimates of the effect of acute (1-day) PM2.5 on cumulative visits over one month, by sector

Notes: This figure displays IV estimates of the effect of a 1-day, 1 $\mu g/m^3$ increase in PM2.5 on cumultaive economic activity over one month, disaggregated by the three largest sectors in the sample: retail trade (25% of visits), accommodation and food services (21%), and recreation (14%). Visit rates are measured as cumulative visits over a time window ranging from 0 to 30 days, as indicated on the x-axis. Points show the estimates, vertical lines indicate 95% confidence intervals, and standard errors are clustered at the county level. Corresponding results in absolute terms (visits per 1,000 people) are shown in Figure C.7.

Figure C.8 presents sector-specific estimates of PM2.5 effects over time for additional industries. Sectors such as other services, finance and insurance, public administration, and information experience an immediate decline, but after one month, their recovery suggests that people eventually make up for lost activities in these sectors. In contrast, transportation and warehousing, wholesale trade, and retail trade exhibit both immediate and sustained declines, highlighting their vulnerability to air pollution. Interestingly, I observe a contemporaneous decline followed by an increase in activities in real estate, educational services, and health care industries over one month. This may be due to housing searches shifting toward cleaner areas in response to poor air quality (Chen et al., 2022; Pan, 2023), educational disruptions such as pollution-induced school closures that increase demand for alternative services outside school (Currie et al., 2009), and health effects that take time to manifest (Simeonova et al., 2021).

Overall, the sector-level dynamics indicate that pollution changes not just the amount but also the structure of economic activity. Losses are concentrated in discretionary sectors such as recreation, which are difficult to make up and therefore imply direct welfare costs. Routine activities like retail and food services are also depressed, creating wider economic effects for local businesses. In contrast, finance, information, and other services tend to rebound, suggesting that some forms of consumption can be delayed or shifted. Increases in real estate, education, and health care highlight compensatory adjustments, as households reallocate activity in response to disruption. Overall, these patterns show that pollution reshapes economic behavior in ways that create lasting welfare losses and uneven sectoral vulnerabilities, with important implications for both policy and business resilience.

5.3 Heterogeneity

A growing literature shows that exposure to air pollution and other environmental risks is unequally distributed across demographic groups (Mohai et al., 2009; Hsiang et al., 2019). To examine whether the effects of air pollution on visits also differ across groups, I estimate the effects separately for counties grouped by age composition, income, and racial composition. County characteristics are measured using 2017 ACS data and compared to the corresponding 2017 national medians. [20] These heterogeneity patterns shed light on potential mechanisms: children reflect biological vulnerability, while income and race highlight socioeconomic resources and constraints.

I begin with heterogeneity by age composition. Children are especially vulnerable to pollution due to ongoing lung development (Dietert et al., 2000; Aragón et al., 2017; Jayachandran, 2009). Counties are divided into two groups based on whether the share of children under five is above or below the median.[21] As shown in Figure 6a, counties with more young children (darker solid line) experience larger and more persistent declines in economic activity, suggesting a stronger behavioral response among communities with a higher proportion of vulnerable populations. This pattern is consistent with a health vulnerability channel, in which parents reduce exposure for children and health shocks take longer to resolve. Notably, since counties with more children also have higher baseline visit rates (76.6 vs. 63.1 visits per 1,000 people), the absolute declines in visits are even larger.[22]

[20] These county groupings may differ along other unobserved dimensions, so the comparisons should not be interpreted as strictly causal. Instead, they provide suggestive evidence on how responses vary across populations with different demographic characteristics.

[21] See Appendix Table C.5 for 1-day estimates.

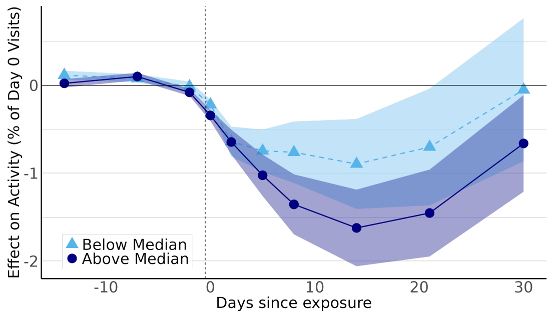
[22] Results in absolute terms are shown in Figure C.9.

Next, I examine heterogeneity by income. Similar to the age analysis, counties are divided into two groups based on whether their median income is above or below the national median. As shown in Figure 6b, high-income counties (darker solid line) experience larger declines in economic activity both contemporaneously and cumulatively over time. One explanation is that higher-income populations are more aware of the health risks associated with pollution and have greater flexibility to adjust their behavior. The larger and more persistent declines in high-income counties cannot be explained by an information channel alone. If avoidance were driven purely by awareness of pollution, we would expect sharper same-day drops but a faster rebound. Instead, the lasting reductions suggest that higher-income populations substitute to alternatives, such as online delivery, which remove the need to make up missed visits.[23] Similar to the case for age composition, since high-income counties also have higher baseline visit rates (71.1 vs. 68.6 visits per 1,000 people), the absolute declines are even larger.

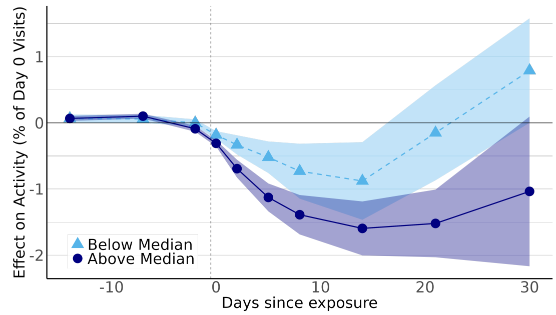
Finally, I examine heterogeneity by racial composition. Counties are grouped based on whether their share of White residents is above or below the median. As shown in Figure 6c, counties with a higher White share (darker solid line) experience a sharper initial reduction in economic activity after pollution exposure, while counties with a lower White share show more muted responses. Prior research indicates that air pollution disproportionately harms minority populations' health (Currie and Walker, 2011; Chay and Greenstone, 2003). One possible explanation is differential avoidance behavior: communities with a higher minority share may engage less frequently in pollution avoidance activities, resulting in prolonged exposure and potentially worse health outcomes. This asymmetry reinforces environmental justice concerns, as disadvantaged populations may be simultaneously more exposed and less able to mitigate exposure. It is worth noting that counties with a higher White share have lower baseline visit rates (63.1 vs. 76.6 visits per 1,000 people) but still experience slightly larger absolute reductions (Figure C.9c).

Taken together, the heterogeneity results suggest that avoidance responses are strongest where biological vulnerability is greater or where awareness of pollution risks and the resources to act on them are higher. This underscores that pollution costs are unevenly distributed, both because exposure is unequal and because the capacity to avoid it differs across groups.

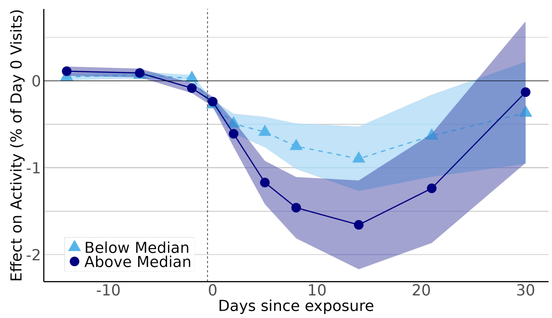
[23] This pattern is also unlikely to reflect medical expense constraints, which are less binding for higher-income populations.



(a) Higher vs. lower child share



(b) Higher vs. lower income



(c) Higher vs. lower White share

Figure 6. IV estimates of the effect of acute PM2.5 exposure on economic activity, by demographic group

Notes: Each point represents an IV estimate from Equation (4) for different subsamples, measuring the effect of acute PM2.5 exposure on economic activity, expressed in percentage terms, across demographic groups. The solid line represents counties with income, child share, or White share above the median, while the dashed line represents those below the median. The cumulative effect is measured over one month, as indicated on the x-axis. Shaded areas denote 95% confidence intervals. All regressions include county-by-month, county-by-year, month-by-year, and day-of-week fixed effects, along with flexible controls for temperature, precipitation, dew point, and wind speed. Additionally, regressions incorporate leads of these weather controls, as well as two leads and two lags of the instruments. Standard errors are clustered at the county level. Results in absolute terms (visits per 1,000 people) are shown in Figure C.9.

5.4 Mechanisms

The conceptual framework in Section 3 highlights two broad channels through which pollution reduces activity. The first is direct health effects: exposure raises the marginal disutility of going out, as individuals experience physical discomfort or must reallocate time to caregiving. The second is avoidance behavior: even in the absence of symptoms, individuals reduce activity when they perceive pollution risks and seek to prevent exposure.Both mechanisms decrease the utility of going out, but they differ in timing: health effects can generate both immediate and persistent reductions, while avoidance primarily amplifies the same-day decline.

Health Exposure to elevated PM2.5 levels can cause acute symptoms such as fatigue, coughing, or chest tightness, and a large literature documents that pollution worsens short-term respiratory and cardiovascular health (Neidell et al., 2023; Schlenker and Walker, 2016; Deryugina et al., 2019; He et al., 2020; Moretti and Neidell, 2011). These acute health shocks may reduce outside activities directly, especially those that require physical effort or take place in crowded environments. In the framework outlined in Section 3, pollution raises the marginal disutility of activity, lowering optimal activity levels. In addition, if household members become sick, time otherwise allocated to work or leisure may be diverted to caregiving, further reducing activity (Aragón et al., 2017; Hanna and Oliva, 2015). Consistent with this channel, I find that counties with more children—who are particularly vulnerable to pollution—exhibit larger and more persistent declines in activity.

Beyond same-day reductions, health effects also generate persistent declines. Symptoms often take time to subside, so individuals may remain less active even after air quality improves. As health recovers, activity partially rebounds, but foregone trips are not fully made up, producing a lasting decline. While health shocks naturally generate persistence, other forces may also contribute. Temporary reductions during polluted periods can lead to habit formation or substitution—for example, households that shift to delivery, streaming, or home exercise may not immediately return to prior routines. The partial rebound observed after about two weeks may also reflect scheduling frictions. These patterns align with the dynamic results in Section 5.2.

Information and Perceptions Avoidance behavior is often triggered not by illness, but by information and perceptions of pollution risk. Individuals may respond to formal air quality warnings, such as EPA's Air Quality Index (AQI) advisories or local Action Day alerts. However, these alerts are rare events, triggered only at high pollution levels, and my results are not driven by them. As shown in Appendix A, responses to AQI alerts are statistically imprecise. More importantly, the reduction in visits remains statistically significant when restricting the sample to days with PM2.5 below 15 $\mu g/m^3$, well below the alert threshold (Table C.6). This indicates that avoidance behavior occurs even in the absence of official warnings, likely reflecting private information from weather apps or home monitors. Consistent with this interpretation, Figure 6 shows stronger responses in higher-income and higher White-share counties, which may reflect greater awareness of pollution risks and a wider ability to adjust daily routines or shift toward alternatives.

Perceptions of air quality may also matter. Pollution particles reduce visibility by scattering and absorbing light, diminishing the clarity and color of what people see. Individuals may use visibility as a salient signal of poor air quality and choose to spend more time indoors on hazy days. In Appendix A, I provide supplementary evidence that days with lower satellite-based visibility are associated with lower visit rates, consistent with this perception channel. While necessarily correlational, this analysis underscores that avoidance may arise not only from direct health burdens but also from how pollution is perceived and communicated.

Budget Constraints Pollution can increase medical spending (Barwick et al., 2024), which in turn may reduce discretionary consumption and activities by tightening household budgets. However, this mechanism is unlikely to be first-order. If budget constraints dominated, one would expect larger declines in lower-income counties, where medical expenses represent a bigger burden. Instead, I find the opposite (Figure 6b): higher-income counties exhibit larger and more persistent declines. This suggests that while budget constraints may operate as a secondary channel, their impact is likely overshadowed by other factors such as awareness of pollution risks and the availability of substitutes.

6 Robustness Checks

In this section, I first test the validity of the IV. IV estimates can be interpreted as the local average treatment effect (LATE) when the monotonicity assumption holds (Angrist and Imbens, 1995). In this paper, this assumption will be satisfied if every county within a geographic cluster group experiences a change in pollution in the same direction when the wind blows from a 90-degree direction bin, and will be violated if some counties experience changes in different directions with other counties within the same cluster group. One way Deryugina et al. (2019) assesses the validity of this assumption is by varying the number of geographic clusters and the sizes of the wind direction bins. I follow a similar approach by changing the number of geographical clusters from 20 to 10 and 30 and reducing the size of wind angle bins from 90 degrees to 60 degrees. In Table 3, column (1) reports the baseline specification; columns (2)-(3) vary the number of geographic clusters; and columns (4)-(6) reduce the wind angle bin size from 90 to 60 degrees. In all cases, the IV estimates are similar to the main specification, supporting the robustness of the main result to different instrument choices.

Table 3. Robustness of IV estimates to instrument choices

	(1)	(2)	(3)	(4)	(5)	(6)
PM2.5 ($\mu g/m^3$)	-0.20***	-0.22***	-0.18***	-0.25***	-0.23***	-0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of geographic clusters	20	10	30	10	20	30
Size of wind angle bins	90°	90°	90°	60°	60°	60°
First-stage F-statistic	87.36	143.36	60.04	93.36	57.51	49.48
R^2	0.86252	0.86123	0.86	0.86	0.86	0.86
Observations	4,495,000	4,495,000	4,495,000	4,495,000	4,495,000	4,495,000
Dependent variable mean	69.85	69.85	69.85	69.85	69.85	69.85

Notes: This table reports the IV estimates from Equations (4) and (5) under alternative instrument choices. The dependent variable is the number of visits per thousand people on the day of exposure. All regressions include county-by-month, county-by-year, day-of-week, and month-by-year fixed effects, as well as flexible weather controls. The baseline model (column (1)) aggregates counties into 20 clusters and wind direction into 90-degree intervals. Standard errors clustered at the county level are reported in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Another underlying assumption of this IV approach is that the variation comes primarily from the pollution that is transported by wind rather than generated locally. If this underlying assumption holds, then the first stage should be weaker on days with low wind speeds and stronger on days with high wind speeds. To further examine the validity of this IV approach, I calculate the first-stage F-statistics separately by quintiles of daily wind speed. As shown in Figure 7, the strength of the first stage increases as wind speed increases. This implies the pollution variation is mainly due to non-local transport by wind, which supports the validity of my approach.

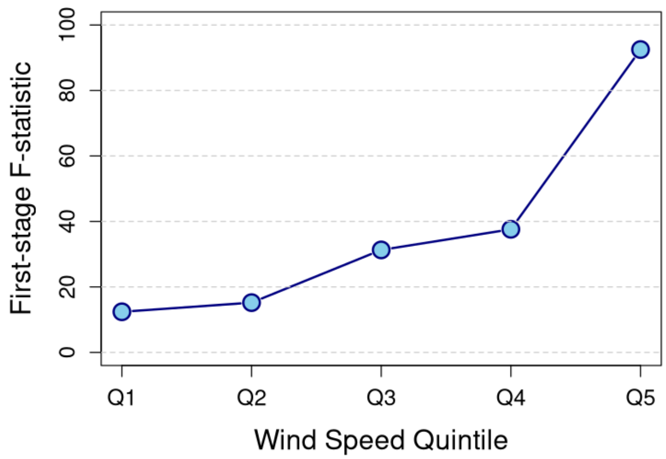


Figure 7. Relationship between the first-stage F-statistics and wind speed

Notes: This figure displays the first-stage F-statistics for five subsamples, each corresponding to a wind speed quintile. The first-stage F-statistics are generally smaller on days with low wind speeds and larger on days with high wind speeds.

Beyond instrument validity, a key identifying assumption is that changes in wind direction affect economic activity only through its impact on pollution levels. This assumption would be violated if wind direction were systematically correlated with unobserved weather conditions that also influence activity. While this cannot be tested directly, I assess its plausibility by varying the specification of weather controls (Table 4). Column (2) omits weather controls entirely, columns (3) and (4) replace weather bins with linear and quadratic controls, and column (5) coarsens the temperature, dew point, and wind speed bins. Across all specifications, the estimated effect remains stable, supporting the validity of the identifying assumption.

Table 4. Robustness of IV estimates to alternative forms of weather controls

	(1)	(2)	(3)	(4)	(5)
PM2.5 ($\mu g/m^3$)	-0.20***	-0.14***	-0.12***	-0.17***	-0.16***
	(0.01)	(0.007)	(0.01)	(0.01)	(0.01)
First-stage F-statistic	87.36	262.53	87.52	80.82	95.85
Dependent variable mean	69.85	69.85	69.85	69.85	69.85
Fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.86	0.86	0.87	0.86	0.86
Observations	4,495,000	4,495,000	4,495,000	4,495,000	4,495,000
Weather Controls					
Baseline	✓				
Linear			✓		
Quadratic				✓	
Less granular bins					✓

Notes: This table reports IV estimates from Equations (4) and (5) using different combinations of weather controls. The dependent variable is the number of visits per thousand people on the day of exposure. All regressions include county-by-year, county-by-month, day-of-week, and month-by-year fixed effects. Column (1) presents the baseline specification, controlling for bins of mean temperature, precipitation, wind speed, dew point, and all observed combinations of these variables. Column (2) omits all weather controls. Column (3) uses linear weather controls instead of bins. Column (4) uses quadratic weather controls. Column (5) uses 5-degree-Celsius temperature bins instead of 3-degree bins. Standard errors clustered at the county level are reported in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Then, I check the robustness of the main specification along several dimensions. First, Table 5 shows that the estimates are stable across different numbers of instrument lags, indicating that the results are not driven by lagged PM2.5 and can be interpreted as the effect of a one-unit increase in daily PM2.5. Second, Table 6 reports estimates with alternative sets of fixed effects, confirming that the results are not driven by seasonal or regional patterns. Third, Table C.9 presents estimates using the log and inverse hyperbolic sine transformations instead of visit rates, showing that the findings are insensitive to the functional form of the dependent variable. Finally, I assess potential spatial and temporal correlation by clustering the standard errors at multiple levels, including county, geographic group, state, and two-way clustering by county and year. As shown in Table C.10, the estimates remain significant across all clustering choices.

Table 5. Robustness of IV estimates to including different instrument lags

	(1) 1 lead and 1 lag	(2) 1 lag	(3) 2 lags	(4) 3 lags	(5) 4 lags
PM2.5 ($\mu g/m^3$)	-0.20***	-0.13***	-0.20***	-0.20***	-0.20***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
# of instruments leads and lags	2	0	1	3	4
First-stage F-statistic	87.36	162.90	87.36	77.71	84.56
R^2	0.86	0.86	0.8	0.86	0.86
Observations	4,495,000	4,501,200	4,495,000	4,488,800	4,482,600
Dependent Variable Mean	69.85	69.85	69.85	69.85	69.85

Notes: This table reports IV estimates from Equations (4) and (5) with different numbers of instrument lags. The baseline model (column (1)) includes 2 leads and 2 lags. The dependent variable is the number of visits per thousand people on the day of exposure. All regressions include county-by-month, county-by-year, day-of-week, and month-by-year fixed effects, as well as flexible weather controls. Standard errors clustered at the county level are reported in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 6. Robustness of IV estimates to alternative forms of fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
PM2.5 ($\mu g/m^3$)	-0.20***	-0.23***	-0.16***	-0.16**	-0.21***	-0.27***
	(0.01)	(0.01)	(0.05)	(0.06)	(0.06)	(0.08)
County-by-year FE	✓	✓	✓			
County-by-month FE	✓	✓				
Month-by-year FE	✓		✓	✓		✓
Day-of-week FE	✓		✓	✓		
State-by-month FE				✓	✓	
State-by-year FE				✓	✓	✓
First-stage F-statistic	87.36	84.77	50.03	62.05	60.24	43.39
R^2	0.86	0.80	0.81	0.31	0.26	0.27
Observations	4,495,000	4,495,000	4,495,000	4,495,000	4,495,000	4,495,000
Dependent variable mean	69.85	69.85	69.85	69.85	69.85	69.85

Notes: This table reports IV estimates from Equations (4) and (5) using different combinations of fixed effects. The dependent variable is the number of visits per thousand people on the day of exposure. Column (1) presents the baseline specification. Standard errors clustered at the county level are reported in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

I have thus far interpreted my estimates as the causal effects of exposure to PM2.5. One potential concern, however, is that other harmful pollutants may be co-transported with PM2.5, potentially confounding the estimated effect. To address this issue, I re-estimate the main specification while including daily concentrations of SO_2, NO_2, and O3 as additional controls. Table C.11 reports the results. The coefficient on PM2.5 remains negative and statistically significant, indicating that the main findings are not driven by co-movements with other pollutants.

The sample period ranges from January 1, 2018 to December 31, 2021, which includes the COVID-19 pandemic that dramatically affected individuals' mobility patterns. To ensure that the results are not influenced by public-health guidance on economic activity, I add an interaction between PM2.5 and an indicator for the COVID-19 period.[24] As shown in Table C.12, the interaction indicates a dampened effect during the COVID-19 period, although both coefficients remain significant. This suggests that the negative impact is not solely driven by pandemic-related restrictions.

As a final robustness check, I consider counties without satellite grid points. In the main specification, I interpolate their PM2.5 levels using inverse distance weighting (IDW) based on the latitude and longitude of the county centroid. Table C.13 shows that the results remain robust when I exclude these counties from the analysis.

7 Conclusion

This paper provides the first large-scale analysis of how PM2.5 affects daily economic activity across the United States. Leveraging changes in wind direction as an instrumental variable, I address the endogeneity of air pollution exposure and find robust evidence that PM2.5 significantly reduces daily visitation rates. Specifically, a 1 $\mu g/m^3$ increase in PM2.5 decreases visit rates by an average of 0.29%, translating into a nationwide annual reduction of approximately 24.6 million trips and an economic cost exceeding $1.1 billion. The effect is not confined to the day of exposure: activity continues to decline over the following two weeks, with cumulative losses roughly doubling the contemporaneous effect before partially recovering. The reductions are widespread across sectors, most pronounced in recreation and entertainment, and larger for outdoor than indoor facilities. Responses also vary significantly across demographic groups: wealthier counties and those with more young children reduce activity more sharply, while minority populations exhibit smaller behavioral responses, suggesting differential ability or willingness to engage in avoidance behavior.

While this study is not without limitations, each limitation also highlights opportunities for future research. First, the analysis primarily captures short- and

[24]The COVID-19 period is defined as March 15, 2020, when many states and cities in the U.S. began implementing lockdowns, stay-at-home orders, and other restrictions to curb the spread of the virus, through December 10, 2020, prior to the FDA's emergency use authorization for the first COVID-19 vaccine.

medium-term behavioral responses, leaving open how households adapt in the long run—a question with important implications for cumulative welfare costs. Second, because the data are aggregated at the county level, individual-level heterogeneity by health status, age, or socioeconomic conditions cannot be fully explored; finer-grained data would allow future work to better characterize these differences. Third, the reduced-form approach captures a composite of avoidance behavior and direct health impacts. Although these channels cannot be separately identified here, the estimates can be interpreted as a conservative lower bound on social costs, since they exclude the broader medical and productivity losses associated with pollution-related illness.

Despite these limitations, this study makes several important contributions. First, it provides the first comprehensive and nationally representative estimates of air pollution's causal impact on daily economic activity, extending prior work that focused on narrower settings or specific activities. Second, the results highlight the central role of behavioral responses: failing to account for these adjustments risks understating the true social costs of pollution. Third, by documenting persistent reductions in activity and heterogeneity across sectors and demographic groups, the analysis underscores the broader welfare consequences of pollution—ranging from losses in physical and psychological well-being to disruptions in key economic sectors.[25] Taken together, these findings suggest that policies improving air quality can yield substantial gains not only through better health outcomes, but also by sustaining the economic and social activities that underpin everyday life.

[25] A simple back-of-the-envelope calculation in Appendix B suggests that, even when considering only recreation visits, the losses amount to hundreds of millions of dollars annually.

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Appendix A Mechanism Analyses

In this appendix, I provide supplementary empirical analyses of two potential mechanisms through which air pollution reduces daily activities. First, individuals may respond directly to pollution information, including national Air Quality Index (AQI) categories and Action Day alerts issued by local governments. A second potential mechanism is that individuals spend more time at home on days with poor visibility. These analyses help illustrate the role of information and perception in shaping avoidance behavior.

Appendix A.1 Pollution Information

AQI Categories A natural source of pollution information comes from the U.S. Environmental Protection Agency's Air Quality Index (AQI). The AQI is a standardized scale ranging from 0 to 500 designed to communicate air quality conditions to the public. Real-time AQI values and associated behavioral guidelines are disseminated through official channels, including the EPA's website (www.airnow.gov) and widely used mobile applications. Table C.7 summarizes the AQI categories, the corresponding PM2.5 concentrations, and the behavioral recommendations.

When PM2.5 levels exceed 35.5 $\mu g/m^3$, corresponding to an AQI of 101, the information system color-codes the pollution level as orange, indicating that air quality is unhealthy for sensitive groups. Most weather apps and websites prominently display advisories under these conditions (see Figure C.10). Although the marginal increase in pollution levels around this threshold is small, pollution information becomes much more salient to the public.

To estimate the causal effects of categorical pollution information and widely disseminated advisories on behavior, I utilize a regression discontinuity (RD) design with PM2.5 concentrations serving as the running variable. The analysis examines outcomes on either side of the 35.5 $\mu g/m^3$ threshold. A crucial assumption for the validity of this approach is the absence of manipulation at this threshold, which is reasonable since PM2.5 data are automatically recorded by air quality monitors. Figure C.11 supports this assumption. Given that AQI advisories are based on EPA monitor data, subsequent analyses employ monitor-based PM2.5 measurements.[26]

Table A.1 summarizes RD estimates across various bandwidths and kernel spec-

[26] Due to the absence of monitors in some counties, the analysis includes 601,894 observations covering January 1, 2018, through December 30, 2021.

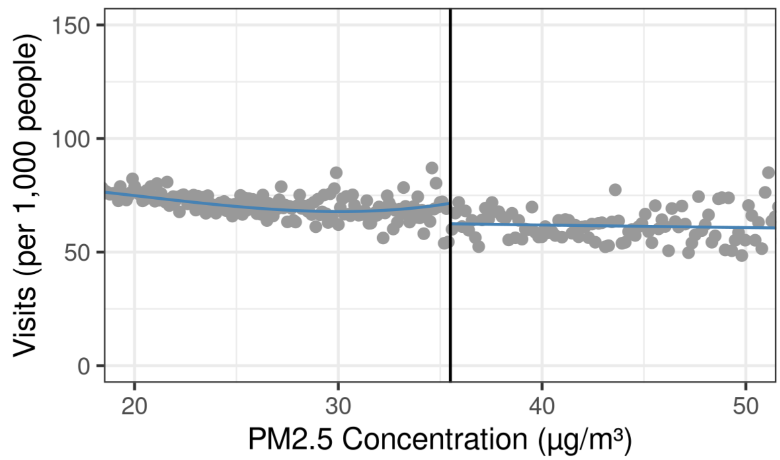
ifications. The results indicate a negative but statistically insignificant effect of AQI advisories on visitation rates. Similarly, Figure A.1 reveals no clear discontinuity at the threshold. This lack of significant findings could result from limited observations around the cutoff, as only 0.34% of data points surpass the AQI threshold of 100. Alternatively, individuals may respond only when advisories indicate much higher pollution levels. Previous research supports this notion, showing stronger behavioral responses at higher pollution thresholds (e.g., AQI of 300).[27]

Appendix Table A.1. RD estimates of AQI advisories

	(1)	(2)	(3)	(4)	(5)	(6)
AQI Advisories	-4.0	-3.0	-2.1	-3.0	-3.2	-1.4
	(3.9)	(2.7)	(1.9)	(3.8)	(2.6)	(1.8)
Kernel	Triangular	Triangular	Triangular	Uniform	Uniform	Uniform
Bandwidth	5	10	20	5	10	20
Dependent variable mean	75.99	75.99	75.99	75.99	75.99	75.99
Observations	691,387	691,387	691,387	691,387	691,387	691,387
Effective observations	1,939	5,744	42,595	1,987	5,863	43,567

Notes: This table presents regression discontinuity (RD) estimates of the effect of AQI advisories on economic activity, using PM2.5 as the running variable with a cutoff at 35.5 $\mu g/m^3$ (equivalent to AQI = 101, unhealthy for sensitive groups). The dependent variable is the number of visits per thousand people on the day of exposure. Estimates are reported for different bandwidth choices and kernel specifications.

[27] For example, Neidell (2009) and Zivin and Neidell (2009) demonstrate significant responses to smog alerts issued for ozone levels equivalent to AQI 300 in California.



Appendix Figure A.1. Visits per 1,000 people by PM2.5 levels around the AQI threshold

Notes: This figure shows binned averages of visitation rates against daily PM2.5 concentrations. The vertical line marks the EPA threshold for "unhealthy for sensitive groups" (35.5 $\mu g/m^3$, AQI=101). Solid lines are polynomial fits estimated separately on each side. No discontinuity is evident.

Action Day Alerts In addition to uniform AQI advisories, Action Day alerts are discretionary warnings issued by local air quality management agencies when air pollution is forecasted to reach unhealthy levels. On Action Days, governments urge the public to reduce pollution by minimizing driving, limiting outdoor activities, and staying indoors. The criteria and timing for Action Day alerts differ substantially across jurisdictions, providing natural variation for evaluating their effectiveness in influencing behavioral responses.

To systematically analyze the effects of Action Day alerts, I obtain a comprehensive dataset from the EPA's AirNow program, covering 346 reporting jurisdictions across cities, counties, metropolitan areas, and states, representing approximately 50% of the U.S. population. To ensure consistency and avoid jurisdictional duplication, data are aggregated at the Core-Based Statistical Area (CBSA) level.

Figure C.12 demonstrates that the probability of Action Day alerts increases with rising daily PM2.5 concentrations. However, fewer than one-fifth of high-pollution days trigger Action Day alerts, providing variation to examine whether these alerts independently influence economic activity, conditional on similar pollution levels.

Table A.2 presents empirical results examining the incremental effect of Action Day alerts on economic activity. Although the estimated magnitude of Action Day alerts is approximately twice that of the PM2.5 effect alone, the estimates are imprecise and statistically insignificant, likely due to the small share (around 1.8%) of Action Days. Moreover, since Action Day alerts are issued in response to forecasted pollution conditions and reflect local agency discretion, the estimates should also be interpreted with caution given their endogenous nature. As an additional robustness check, I estimate effects excluding observations with consecutive Action Days, and the results remain very similar (Columns (3) and (4) of Table A.2).

Appendix Table A.2. Additional effect of Action Days on economic activity

	All Days		Exclude Consecutive Action Days	
	(1)	(2)	(3)	(4)
PM2.5 ($\mu g/m^3$)	-0.10***	-0.09***	-0.12***	-0.12***
	(0.02)	(0.02)	(0.03)	(0.03)
Action Day Alerts		-0.22		-0.15
		(0.32)		(0.26)
First-stage F-statistic	12.2	12.2	14.7	14.7
Dependent variable mean	79.8	79.8	80.0	80.0
Fixed effects	Yes	Yes	Yes	Yes
R^2	0.88	0.88	0.87	0.87
Observations	428,352	428,352	422,983	422,983

Notes: This table reports IV estimates from Equations (4) and (5), examining the additional effect of Action Day advisories. The dependent variable is the number of visits per thousand people at the CBSA level on the day of exposure. All regressions include CBSA-by-month, CBSA-by-year, day-of-week, and month-by-year fixed effects, as well as flexible weather controls. Columns (1) and (2) report results with and without controls for Action Day advisories, while columns (3) and (4) repeat the analysis excluding consecutive Action Day sequences. Standard errors clustered at the CBSA level are reported in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Appendix A.2 Visibility

Perceptions of air quality may also be shaped by visibility. The same pollutants that contribute to PM2.5 can also reduce visibility: airborne particles impair visibility by altering how light is absorbed and scattered in the atmosphere, reducing the clarity and color of what we see.[28] When visibility is low, people might perceive that the air quality is poor and choose to spend more time at home instead of going out.

To examine whether reduced visibility serves as a mechanism through which pollution affects economic activity, I use satellite-based visibility data from the NCEP

[28]Source: https://www.epa.gov/sites/default/files/2015-05/documents/haze_brochure_20060426.pdf. Accessed June 10, 2024.

North American Regional Reanalysis (NARR) database.[29] I implement a three-step procedure. First, I instrument PM2.5 using wind direction, as in Equation (5). Second, I test whether PM2.5 causally reduces visibility by estimating:

$$\text{Visibility}_{ct} = \rho \cdot \widehat{\text{PM2.5}}_{ct} + \mathbf{X}'_{ct}\gamma + \sigma_{cy} + \eta_{cm} + \mu_w + \psi_{my} + \epsilon_{ct} \tag{6}$$

Finally, I regress visit rates on visibility while controlling for instrumented PM2.5. This allows me to examine whether visibility, after controlling for the direct effect of PM2.5, provides additional explanatory power for economic activity. However, since visibility itself is not instrumented, this approach provides correlational evidence rather than causal estimates regarding the relationship between reduced visibility and lower economic activity.[30] Specifically, I estimate:

$$\frac{Y_{ct}}{\text{Pop}_c} = \lambda \cdot \text{Visibility}_{ct} + \kappa \cdot \widehat{\text{PM2.5}}_{ct} + \mathbf{X}'_{ct}\gamma + \sigma_{cy} + \eta_{cm} + \mu_w + \psi_{my} + \nu_{ct} \tag{7}$$

The results are presented in Table A.3. Column (1) shows that PM2.5 significantly reduces visibility: a 1 $\mu g/m^3$ increase in PM2.5 leads to a 0.05 km decrease in visibility on average.[31] Column (2) indicates that reduced visibility is correlated with lower daily economic activity: a 1 km reduction in visibility is associated with a decrease of 0.14 visits per 1,000 people on average. These findings are consistent with Keiser et al. (2018), who find that visitation to national parks declines on days with poor visibility.

[29] See https://psl.noaa.gov/data/gridded/data.narr.html. Accessed July 18, 2024.

[30] Controlling for instrumented PM2.5 helps account for other behavioral or physiological channels through which pollution may directly affect economic activity.

[31] To account for the possibility of a nonlinear relationship between PM2.5 and visibility, I restrict the sample to relatively clean days with PM2.5 concentrations below 15 $\mu g/m^3$. As shown in Table C.8, the estimates remain consistent in direction and magnitude, indicating that the relationship is not driven solely by high-pollution days.

Appendix Table A.3. Visibility as a Mechanism: Effect of PM2.5 on Visibility and Visits

	(1) Visibility (km)	(2) Visits (per 1,000 people)
Visibility (km)		0.14***
		(0.004)
$\widehat{PM2.5}$ ($\mu g/m^3$)	-0.05***	-0.20***
	(0.01)	(0.01)
First-stage F-statistic	87.36	87.36
Dependent variable mean	17.55	69.85
Fixed effects	Yes	Yes
R^2	0.55	0.86
Observations	4,495,000	4,495,000

Notes: This table reports results from the three-step mechanism analysis. Column (1) shows the effect of instrumented PM2.5 on visibility (Equation (6)), and Column (2) shows the effect of visibility on visit rates, controlling for instrumented PM2.5 (Equation (7)). All regressions include county-by-month, county-by-year, day-of-week, and month- by-year fixed effects, as well as flexible weather controls. The dependent variable mean in Column (1) is average visibility (in kilometers), and in Column (2) is average visits per 1,000 people. Standard errors are clustered at the county level. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Appendix B Welfare Analysis

To illustrate the potential welfare implications of the observed declines in daily activities, I provide a simple back-of-the-envelope calculation. This exercise should be interpreted with caution and viewed as a lower bound. It relies on willingness-to-pay (WTP) values for recreation activities, which are the closest sector with well-established valuation estimates, but do not capture the full range of affected activities such as shopping, dining, accommodation, and healthcare.

Rosenberger (2016) reports an average per-day WTP for recreation of approximately \$93.89 (updated to 2022 dollars). Applying this value to the estimated annual reduction in recreation visits (about 1.28 million trips) yields an implied welfare loss of roughly \$120 million per year.[32] Because this calculation covers only recreation—which represents 13.6% of all trips in my data—it almost certainly understates the true welfare costs of pollution-induced behavioral changes. Losses in other large sectors such as retail trade and accommodation and food services are

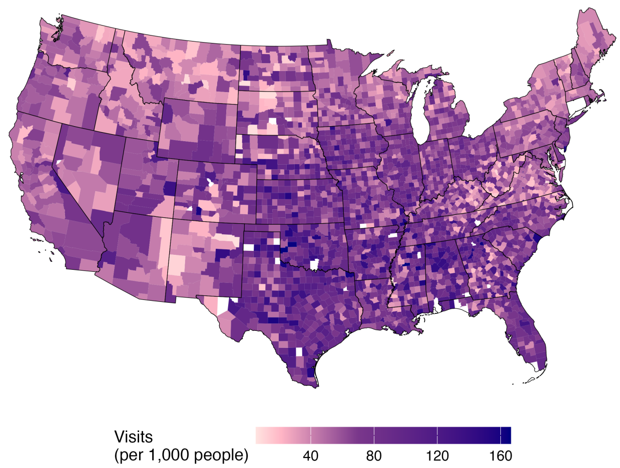
[32] The annual reduction is calculated as 0.00641 visits per person $\times$ 331.9 million people $\times$ 12 months $\approx$ 1.28 million trips annually.

not valued here, and reductions in daily activities may also carry additional health and psychological costs (e.g., obesity, depression).

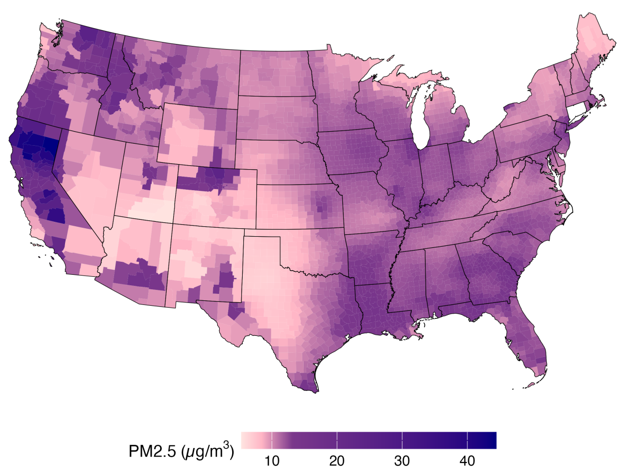
The purpose of this exercise is not to provide a precise estimate, but rather to demonstrate that even partial valuation of lost activities produces non-trivial welfare costs. Future research combining consumer surplus estimates across multiple sectors would allow a more comprehensive accounting of the economic losses from pollution-induced behavioral changes, but this is beyond the scope of this study.

Relative to the World Bank's estimate of \$886.5 billion in U.S. welfare costs from air pollution in 2016 (\$1,081 billion in 2022 USD), my figure is small. However, the two are not directly comparable: the World Bank's figure reflects comprehensive health and environmental damages, whereas my calculation quantifies only economic costs from daily activity changes. A more relevant benchmark comes from other studies of avoidance behavior: Zhang and Mu (2018) estimate the cost of face-mask purchases during heavily polluted periods at about \$187 million, and Fan (2024) estimate the cost of pollution-induced physical inactivity at \$550 million in 2017 (\$656 million in 2022 USD). My back-of-the-envelope estimate for recreation alone falls between these estimates, and the overall economic impact is likely much larger given the broad scope of activities affected.

Appendix C Additional Figures and Tables



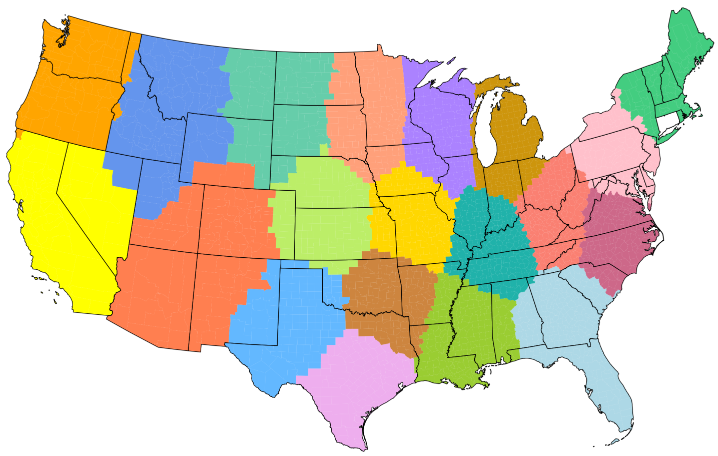
(a) County-level Visit Rates



(b) County-level PM2.5 Concentration

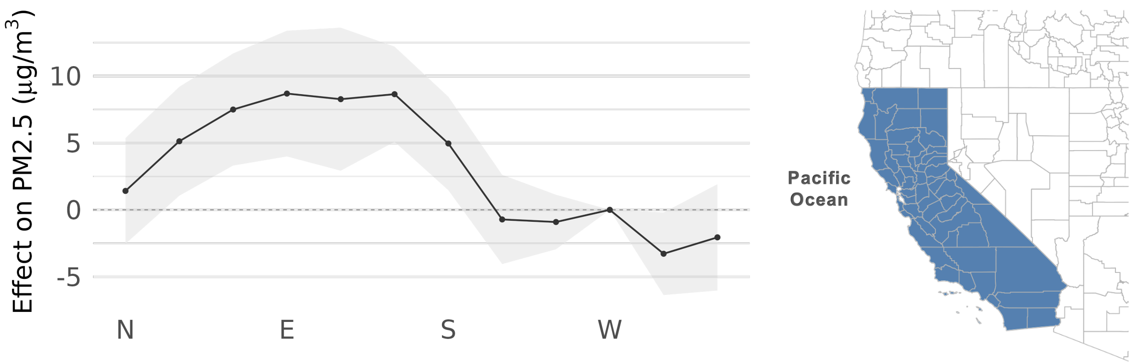
Appendix Figure C.1. County-level visit rates and PM2.5 concentrations

Notes: This figure displays average daily county averages for the number of visits (top panel) and PM2.5 concentration (bottom panel) from January 1, 2018, to December 30, 2021. As a few counties do not have any visitation data, there are some missing values in the figure.



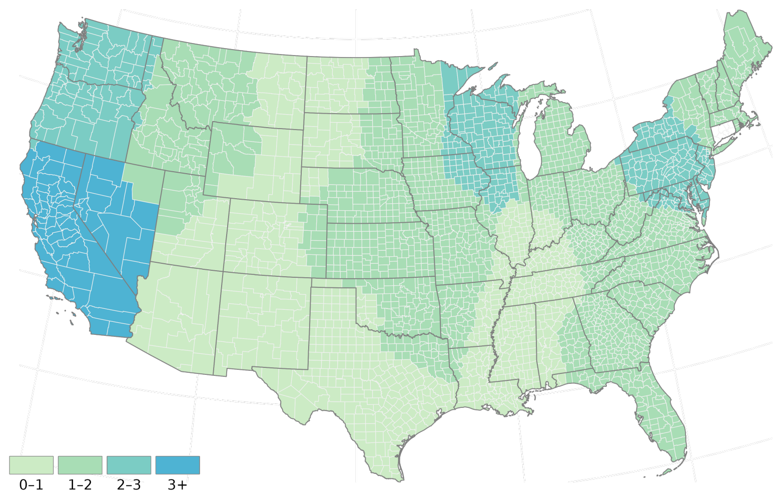
Appendix Figure C.2. K-means clustering result

Notes: This figure displays the K-means clustering result based on latitude and longitude. As a few counties do not have any visitation data for leisure facilities from SafeGraph, there are some missing values in the figure. There are 20 spatial groups in total, and each of them is represented by a different color. After clustering, π_b^g in Equation (5) can vary across geographic regions.



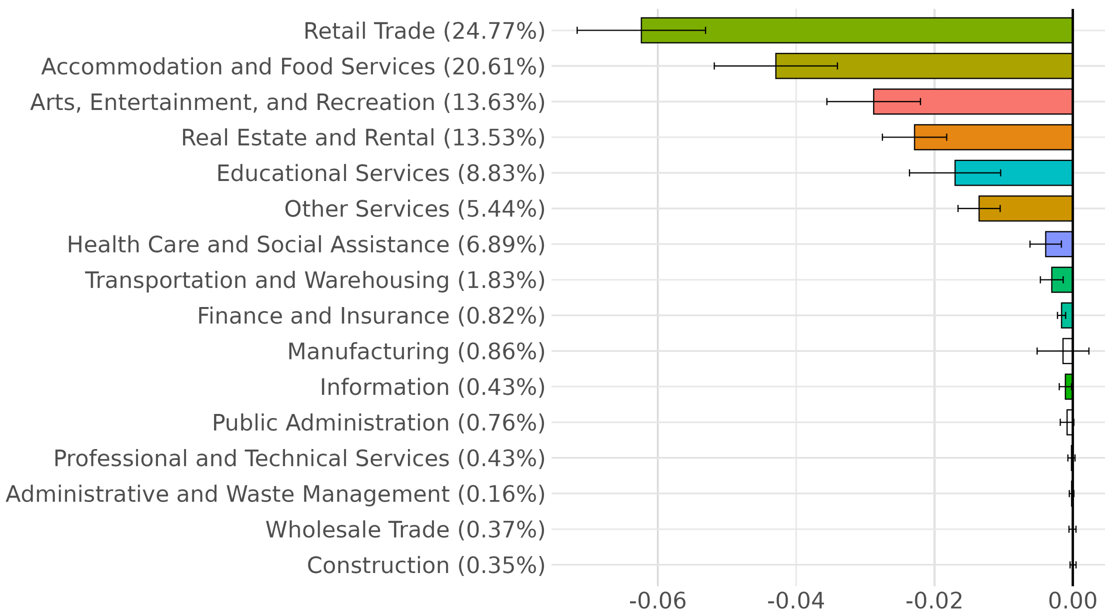
Appendix Figure C.3. The relationship between wind direction and PM2.5 concentration in California

Notes: The graph on the left plots the relationship between PM2.5 concentrations and wind direction in California. Wind direction describes where the wind is blowing *from*, with "N" indicating north, "E" indicating east, etc. The points report coefficient estimates from a regression of PM2.5 on wind direction measured in 30-degree angle bins; wind from the west ("W") is the omitted reference category. The shaded area shows the 95% confidence interval. The specification includes county-by-month, county-by-year, month-by-year, and day-of-week fixed effects, along with flexible weather controls. This figure illustrates that winds from the Pacific Ocean (west) are associated with lower pollution, while winds from the east and southeast are associated with higher pollution.



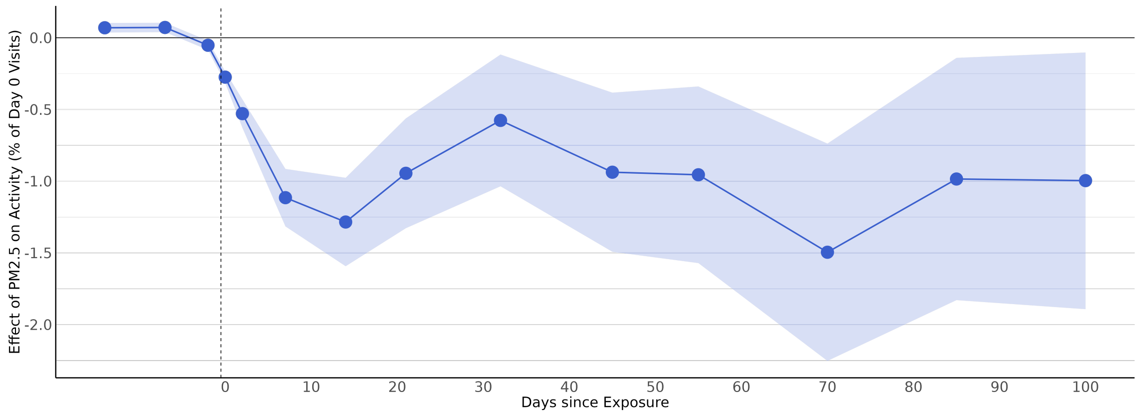
Appendix Figure C.4. Strength of the first stage by geographic group

Notes: This map shows the strength of the first stage for each of the 20 geographic groups used in the main estimation sample. Strength is measured as the difference in predicted PM2.5 concentration ($\mu g/m^3$) between the most and least polluting wind direction bins, where predictions are obtained from the first-stage specification in Equation (5). The 20 geographic clusters are shown in Figure C.2.



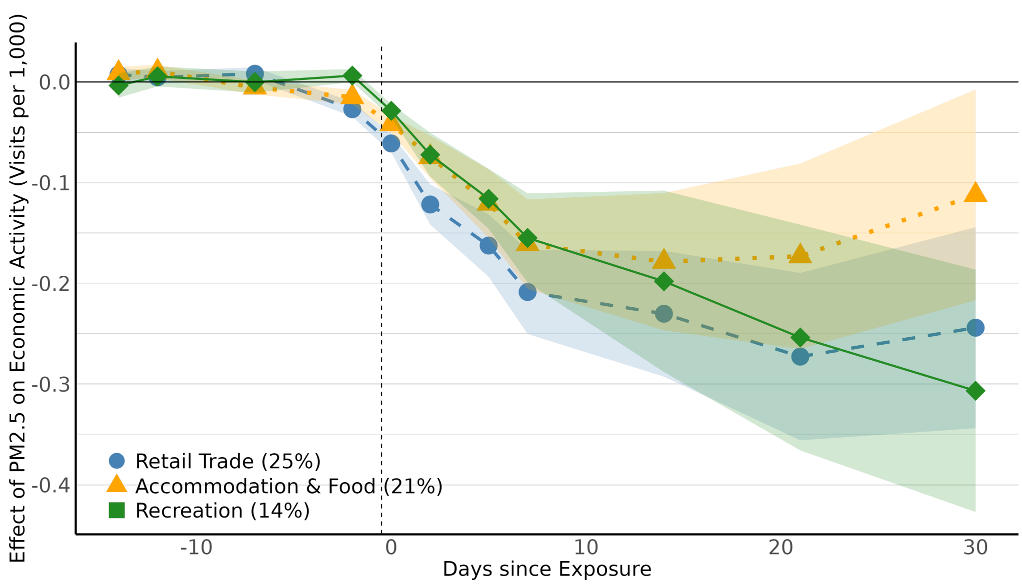
Appendix Figure C.5. Absolute effects (visits per thousand) by 2-digit NAICS codes

Notes: This figure displays the heterogeneous treatment effects of air pollution on daily activities across various industries, categorized by their 2-digit NAICS codes. Each bar represents an IV estimate from Equation (4) of the effect of 1-day PM2.5 exposure on same-day visits for a particular economic sector. The percentage following each industry name indicates the share of raw visits that the industry represents in the sample. Bars represent the estimated effects, with horizontal lines indicating 95% confidence intervals. Industries with raw visits accounting for less than 0.2% are omitted due to high variance. Sectors with statistically insignificant estimates are shown in white. The relative effect as a percentage of the sector's average same-day visits is shown in Figure 1.



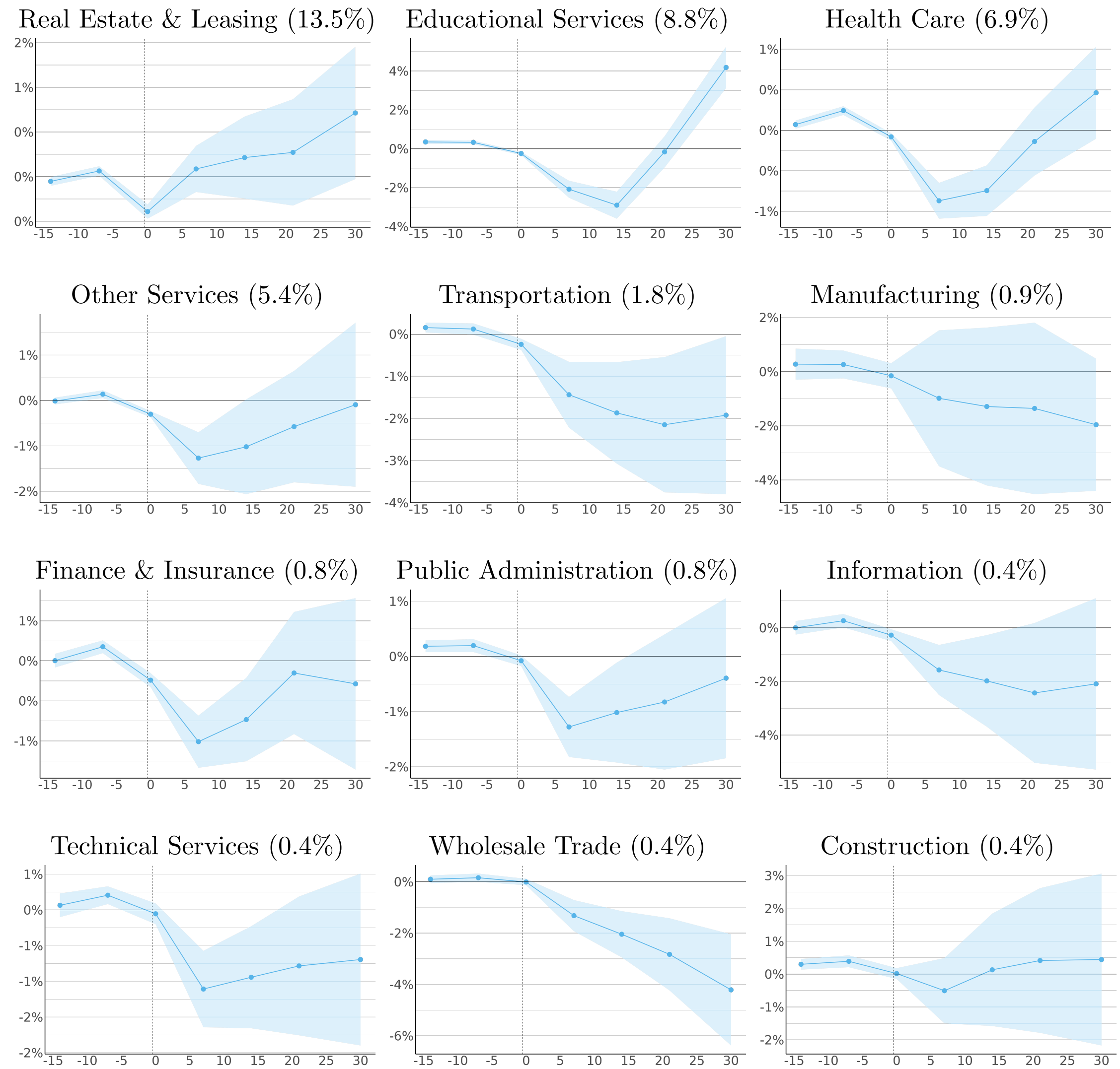
Appendix Figure C.6. IV estimates of effect of acute (1-day) PM2.5 on cumulative economic activity up to 100 days following exposure

Notes: This figure displays IV estimates of the effects of a 1-day, 1 $\mu g/m^3$ increase in PM2.5 on economic activity up to 100 days after exposure. Effects are expressed as a percentage of day 0 visits. Visit rates are measured as cumulative visits over windows ranging from 1 to 100 days, as indicated on the x-axis. Points denote the estimates, vertical lines denote the 95% confidence intervals, and standard errors are clustered at the county level.



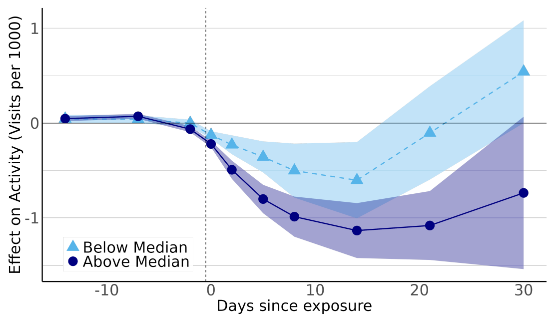
Appendix Figure C.7. IV estimates of the effects of acute (1-day) PM2.5 exposure on cumulative visits per 1,000 people over one month, by sector (absolute terms)

Notes: This figure displays IV estimates of the effects of a 1-day, 1 $\mu g/m^3$ increase in PM2.5 on economic activity, disaggregated by the three largest sectors in the sample: retail trade, accommodation and food services, and recreation. Results are shown in absolute terms (levels), measured as cumulative visits per 1,000 people over a time window ranging from 0 to 30 days, as indicated on the x-axis. Points show the estimates, and vertical lines indicate 95% confidence intervals. Standard errors are clustered at the county level. Corresponding results in percentage terms are presented in Figure 5.

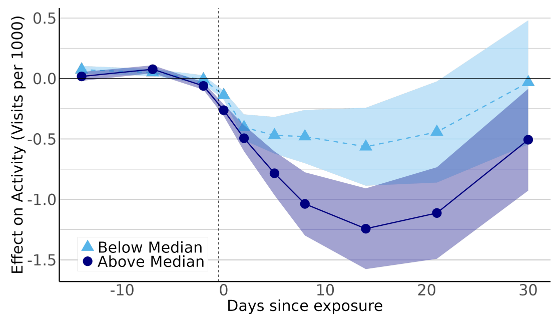


Appendix Figure C.8. IV estimates of the effects of acute PM2.5 exposure on economic activity, by sector

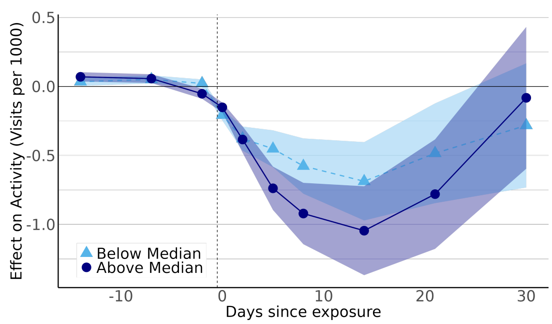
Notes: Each point represents an IV estimate from Equations (4) and (5), measuring the effect of acute PM2.5 exposure on economic activity in percentage terms across 15 industries. The cumulative effect is measured over a time window ranging from 1 to 30 days, as indicated on the x-axis. Shaded areas represent 95% confidence intervals. All regressions include county-by-month, county-by-year, month-by-year, and day-of-week fixed effects, as well as flexible controls for temperature, precipitation, wind speed, and dew point. Standard errors are clustered by county. *Some industry names are shortened to conserve space.*



(a) Higher vs Lower Income



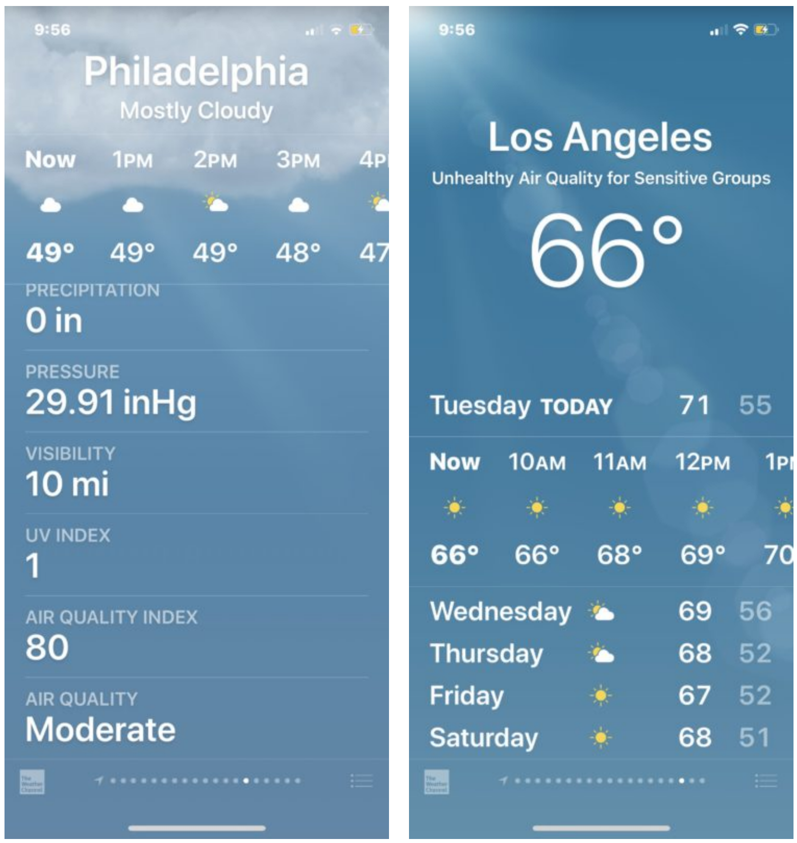
(b) Higher vs Lower Children Share



(c) Higher vs Lower White Share

Appendix Figure C.9. IV estimates of the effects of acute PM2.5 exposure on economic activity, by demographic group (absolute terms)

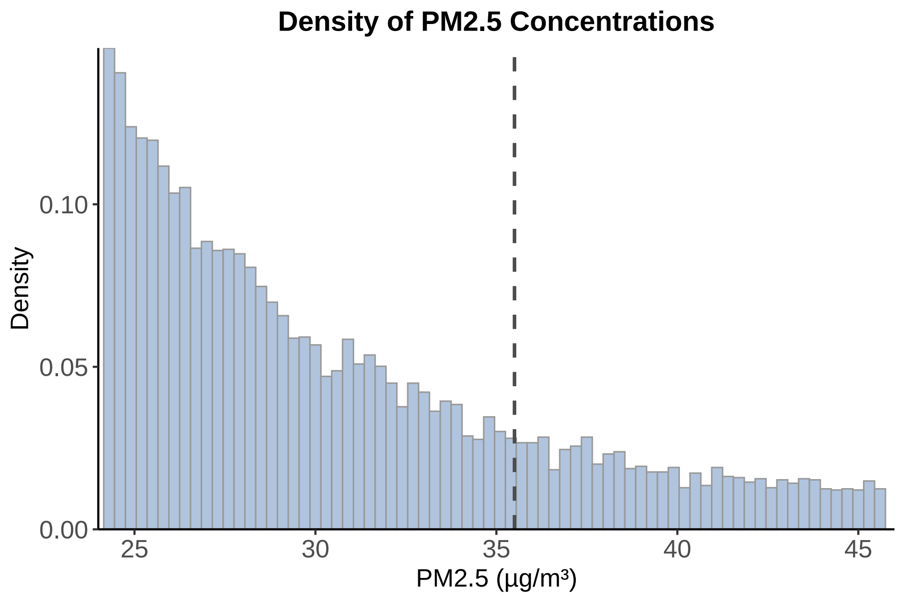
Notes: Each point represents an IV estimate from Equation (4) for different subsamples, measuring the effect of acute (1-day) PM2.5 exposure on economic activity in absolute terms (visits per 1,000 people) across demographic groups. The solid line represents counties with median income, child population share, or white population share above the national median, while the dashed line represents counties below the median. The cumulative effect is measured over one month following exposure, as indicated on the x-axis. Shaded areas denote 95% confidence intervals. All regressions include county-by-month, county-by-year, month-by-year, and day-of-week fixed effects, along with flexible controls for temperature, precipitation, dew point, and wind speed. Additionally, regressions incorporate leads of these weather controls, as well as two leads and two lags of the instruments. Standard errors are clustered at the county level. Corresponding results in percentage terms are presented in Figure 6.



(a) when AQI ≤ 100 (b) when AQI > 100

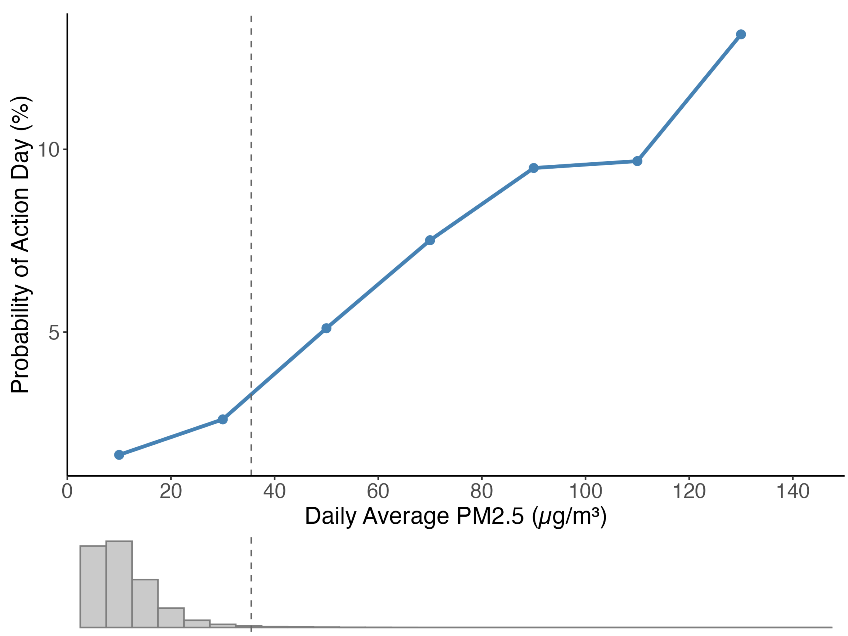
Appendix Figure C.10. Example: air quality information in the iPhone Weather app

Notes: This figure displays the iPhone Weather app interface when AQI $\leq$ 100 (left panel) and AQI $>$ 100 (right panel). When AQI $\leq$ 100, no air quality message appears at the top of the Weather app overview, and users must scroll down to find the information. When AQI $>$ 100, the app prominently displays an air quality warning at the top of the interface. *Source:* https://osxdaily.com/2018/11/20/get-air-quality-info-iphone-weather/



Appendix Figure C.11. No evidence of manipulation at the threshold

Notes: This figure displays the density of daily PM2.5 concentration. The vertical dashed red line at 35.5 $\mu g/m^3$ indicates the EPA-defined threshold for air quality classified as "unhealthy for sensitive groups" (AQI = 101). The smooth distribution around this cutoff suggests no evidence of manipulation at the threshold.



Appendix Figure C.12. Probability of Action Day issuance near the PM2.5 threshold

Notes: This figure plots the share of county-days with an Air Quality "Action Day" advisory against daily average PM2.5 concentration. The vertical dashed line at 35.5 $\mu g/m^3$ indicates the EPA-defined threshold for air quality classified as "unhealthy for sensitive groups." The lower histogram shows the distribution of PM2.5 observations in the sample.

Appendix Table C.1. Share of raw visits by 2-digit NAICS codes

NAICS Codes	Description	Raw visits	Share (%)
44-45	Retail Trade	9,146,929,016	24.77
72	Accommodation and Food Services	7,610,742,956	20.61
71	Arts, Entertainment, and Recreation	5,034,071,398	13.63
53	Real Estate and Rental and Leasing	4,996,089,773	13.53
61	Educational Services	3,261,648,196	8.83
62	Health Care and Social Assistance	2,543,964,413	6.89
81	Other Services	2,010,628,936	5.44
48-49	Transportation and Warehousing	676,689,537	1.83
31-33	Manufacturing	317,021,279	0.86
52	Finance and Insurance	303,659,378	0.82
92	Public Administration	279,409,983	0.76
51	Information	160,409,689	0.43
54	Professional, Scientific, and Technical Services	158,697,298	0.43
42	Wholesale Trade	136,210,405	0.37
23	Construction	130,696,514	0.35
55	Management of Companies and Enterprises	72,815,213	0.20
56	Administrative and Support and Waste Management	59,912,819	0.16
22	Utilities	28,890,736	0.08
11	Agriculture, Forestry, Fishing and Hunting	2,093,013	0.01
21	Mining, Quarrying, and Oil and Gas Extraction	185,256	0.00

Appendix Table C.2. Selected studies on the impact of air pollution on activities

Study	Outcome	Pollution measure	Effect
Entertainment & Recreation			
Fan (2024)	Outdoor exercise in China	10 $\mu g/m^3$ increase in PM2.5	1.4% reduction
Keiser et al. (2018)	Visits to U.S. national parks	1 ppb increase in ozone	3.9% reduction
Zivin and Neidell (2009)	Visits to zoos and observatory in LA	Ozone alert	5–8% reduction
Janke (2014)	Visits to Bristol Zoo (members)	Air pollution alert	6% reduction
Retail Trade			
Sun et al. (2019)	Visits to shopping centers in Beijing	10% increase in PM2.5	0.1% reduction
Addoum et al. (2023)	Visits to retail establishments in the US	Medium-heavy smoke day	0.37% reduction
Accommodation & Food			
Sun et al. (2019)	Visits to restaurants in Beijing	10% increase in PM2.5	0.15% reduction
Gao et al. (2020)	Visits to restaurants in Beijing	1% increase in PM2.5	0.065% reduction
Information			
He et al. (2016)	Movie theater admissions in China	Air pollution index	2.8% reduction
Educational Services			
Currie et al. (2009)	School absences in Texas	Additional high-CO day	5–9% increase
Chen et al. (2000)	School absences in Washoe County	50 ppb increase in ozone	13% increase
Chen et al. (2000)	School absences in Washoe County	1 ppm increase in CO	3.8% increase
Gilliland et al. (2001)	School absences (illness) in Southern California	20 ppb increase in ozone	63% increase
Healthcare			
Liu et al. (2022)	Visits to health facilities in China	1 $\mu g/m^3$ increase in PM2.5	1.8% reduction
Janke (2014)	Hospital admissions in the UK	1% increase in ozone	0.1% increase
Ren et al. (2021)	Hospital admissions in Wuhan, China	10% increase in PM2.5	1.25% increase
Dardati et al. (2024)	ER visits in Chile	1 $\mu g/m^3$ increase in PM2.5	0.03–0.07% increase
Deryugina et al. (2019)	ER visits in the US	1 $\mu g/m^3$ increase in PM2.5	0.06% increase
Schlenker and Walker (2016)	Asthma ER visits in California	1 SD increase in CO	33% increase

Appendix Table C.3. Share of raw visits in the recreation sector

NAICS	Description	Raw visits	Share (%)
712190	Nature Parks and Other Similar Institutions	2,610,937,377	51.97
713940	Fitness and Recreational Sports Centers	908,175,772	18.08
713910	Golf Courses and Country Clubs	525,323,866	10.46
713990	All Other Amusement and Recreation Industries	187,873,033	3.74
713110	Amusement and Theme Parks	184,452,834	3.67
711211	Sports Teams and Clubs	126,947,155	2.53
712110	Museums	93,538,708	1.86
711310	Promoters of Performing Arts and Events	91,428,501	1.82
713210	Casinos (except Casino Hotels)	87,878,401	1.75
712120	Historical Sites	65,689,209	1.31
713950	Bowling Centers	56,054,357	1.12
713920	Skiing Facilities	26,600,467	0.53
712130	Zoos and Botanical Gardens	24,056,950	0.48
713930	Marinas	17,077,159	0.34
713120	Amusement Arcades	6,400,510	0.13
713290	Other Gambling Industries	4,858,269	0.10
711212	Racetracks	4,849,757	0.10
711219	Other Spectator Sports	915,133	0.02
711130	Musical Groups and Artists	528,696	0.01
711190	Other Performing Arts Companies	364,952	0.01
711510	Independent Artists, Writers, and Performers	70,944	0.00
711110	Theater Companies and Dinner Theaters	33,414	0.00
711410	Agents and Managers for Artists	30,905	0.00

Appendix Table C.4. Share of raw visits in the health care sector

NAICS	Description	Raw visits	Share (%)
6221	General Medical and Surgical Hospitals	602,393,987	24.73
6213	Offices of Other Health Practitioners	391,980,708	16.09
6244	Child Day Care Services	349,496,920	14.35
6211	Offices of Physicians	317,171,391	13.02
6212	Offices of Dentists	226,457,069	9.30
6231	Nursing Care Facilities (Skilled Nursing Facilities)	156,062,572	6.41
621492	Kidney Dialysis Centers	61,429,935	2.52
6223	Specialty (except Psychiatric and Substance Abuse) Hospitals	49,666,480	2.04
6233	Assisted Living Facilities for the Elderly	43,721,328	1.80
624190	Other Individual and Family Services	39,871,875	1.64
6214	Outpatient Care Centers	39,677,848	1.63
6216	Home Health Care Services	37,830,065	1.55
6215	Medical and Diagnostic Laboratories	36,241,509	1.49
624110	Child and Youth Services	21,330,836	0.88
6242	Community Food and Housing, and Emergency Relief Services	16,862,249	0.69
6219	Other Ambulatory Health Care Services	13,277,127	0.55
621498	All Other Outpatient Care Centers	13,132,241	0.54
621493	Freestanding Ambulatory Surgical and Emergency Centers	8,481,763	0.35
624120	Services for the Elderly and Persons with Disabilities	6,366,018	0.26
6222	Psychiatric and Substance Abuse Hospitals	3,974,312	0.16

Appendix Table C.5. Heterogeneous effects of PM2.5 across demographic groups, one-day estimates

	(1)	(2)
Panel A: By age group		
PM2.5 ($\mu g/m^3$)	-0.10***	-0.10**
	(0.02)	(0.04)
PM2.5 × 1{Pct. Children > Median}	-0.24***	
	(0.05)	
PM2.5 × 1{Pct. Children > 3rd Quartile}		-0.36***
		(0.08)
Panel B: By income group		
PM2.5 ($\mu g/m^3$)	-0.08***	-0.11***
	(0.03)	(0.02)
PM2.5 × 1{Income > Median}	-0.18***	
	(0.03)	
PM2.5 × 1{Income > 3rd Quartile}		-0.25***
		(0.04)
Panel C: By race group		
PM2.5 ($\mu g/m^3$)	-0.16***	-0.16***
	(0.02)	(0.02)
PM2.5 × 1{Pct. White > Median}	-0.09***	
	(0.03)	
PM2.5 × 1{Pct. White > 3rd Quartile}		-0.16***
		(0.04)
First-stage F-statistics	83.53	83.53
Dependent variable mean	69.85	69.85
Fixed effects	Yes	Yes
R^2	0.87	0.87
Observations	4,493,550	4,493,550

Notes: This table reports the effects of daily PM2.5 on daily activity for different demographic groups using Equations (4) and (5). The dependent variable is the number of visits per thousand people on the day of exposure. All regressions control for bins of mean temperature, precipitation, wind speed, and dew point, as well as two lags of these weather controls. Fixed effects include county-by-year, county-by-month, day-of-week, and month-by-year fixed effects. The dummy variable **1**{Pct. Children > Median} equals 1 (**1**{Pct. Children > 3rd Quartile} = 1) if the percentage of children in county c is above the national median (third quartile). Similarly, **1**{Income > Median} and **1**{Income > 3rd Quartile} are dummies for per capita personal income, and **1**{Pct. White > Median} and **1**{Pct. White > 3rd Quartile} are dummies for the percentage of the white population. Standard errors are clustered at the county level. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Appendix Table C.6. Robustness to PM2.5 cutoff restrictions

	(1) Visits (per 1,000 people)	(2) Visits (per 1,000 people)
PM2.5 ($\mu g/m^3$)	-0.35***	-0.25***
	(0.03)	(0.02)
PM2.5 Cutoff ($\mu g/m^3$)	15	25
First-stage F-statistics	602.14	805.22
Dependent variable mean	69.85	69.85
Fixed effects	Yes	Yes
R^2	0.86	0.87
Observations	3,522,564	4,300,033

Notes: This table shows robustness to restricting the sample to days with PM2.5 concentrations below specific thresholds. Column (1) restricts to days with PM2.5 below 15 $\mu g/m^3$, well below the EPA's Air Quality Index threshold for official warnings. Column (2) restricts to days with PM2.5 below 25 $\mu g/m^3$. The dependent variable is the number of visits per 1,000 people on the day of exposure. All regressions include county-by-month, county-by-year, day-of-week, and month-by-year fixed effects, as well as flexible weather controls. Standard errors clustered at the county level are reported in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Appendix Table C.7. AQI categories and corresponding PM2.5 concentrations

Category	Designated color	AQI	PM2.5 concentration ($\mu g/m^3$)
Good	Green	0-50	0.0-12.0
Moderate	Yellow	51-100	12.1-35.4
Unhealthy for Sensitive Groups	Orange	101-150	35.5-55.4
Unhealthy	Red	151-200	55.5-150.4
Very Unhealthy	Purple	201-300	150.5-250.4
Hazardous	Maroon	301-500	250.5-500

Source: National Ambient Air Quality Standards for Particle Pollution Fact Sheet. Available at: https://www.epa.gov/sites/default/files/2016-04/documents/2012_aqi_factsheet.pdf. Accessed February 25, 2023.

Appendix Table C.8. Visibility as a Mechanism: Robustness to PM2.5 Restrictions

	(1) Visibility (km)	(2) Visits (per 1,000 people)
Visibility (km)		0.12***
		(0.01)
$\widehat{PM2.5}$ ($\mu g/m^3$)	-0.06***	-0.37***
	(0.01)	(0.02)
First-stage F-statistics	747.15	679.80
Dependent Variable Mean	17.52	69.85
Fixed Effects	Yes	Yes
R^2	0.60	0.86
Observations	3,522,564	3,522,564

Notes: This table reports results when restricting the sample to days with PM2.5 concentrations below 15 $\mu g/m^3$. Column (1) shows the effect of instrumented PM2.5 on visibility, and Column (2) shows the effect of visibility on visit rates, controlling for instrumented PM2.5. All regressions control for temperature, precipitation, wind speed, and dew point, including two lags of each weather variable. The dependent variable mean in Column (1) refers to visibility in kilometers, and in Column (2) to the average number of visits per 1,000 people. Fixed effects include county-by-year, county-by-month, day-of-week, and month-by-year. Standard errors are clustered at the county level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Appendix Table C.9. Robustness to Including Different Forms of Outcome

	Visits (per 1,000 people) (1)	log(visit rate) ×100 (2)	IHS(visits) ×100 (3)
PM2.5 ($\mu g/m^3$)	-0.20***	-0.38***	-0.38***
	(0.01)	(0.02)	(0.02)
First-stage F-statistics	87.36	87.36	87.36
Dependent variable mean	69.85	69.85	69.85
Fixed effects	Yes	Yes	Yes
R^2	0.86	0.89	0.99
Observations	4,495,000	4,494,488	4,495,000

Notes: This table reports OLS and IV estimates based on Equation (4) and Equation (5), with the dependent variable transformed using either the log of visit rates or the inverse hyperbolic sine (IHS) of visits. The main specification uses visits per thousand people on the day of exposure as the outcome. All regressions include county-by-month, county-by-year, day-of-week, and month-by-year fixed effects, as well as flexible weather controls. Standard errors clustered at the county level are reported in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Appendix Table C.10. Robustness to alternative clustering levels

	(1)	(2)	(3)	(4)
PM2.5 ($\mu g/m^3$)	-0.20***	-0.20***	-0.20***	-0.20**
	(0.01)	(0.07)	(0.06)	(0.06)
Clustering level(s)	County	Geographic group	State	County and year
First-stage F-statistics	87.36	87.36	87.36	87.36
R^2	0.86	0.86	0.86	0.86
Observations	4,495,000	4,495,000	4,495,000	4,495,000
Dependent variable mean	69.85	69.85	69.85	69.85

Notes: This table reports IV estimates from Equations (4) and (5) with standard errors clustered at different levels. The dependent variable is the number of visits per 1,000 people on the day of exposure. All regressions include county-by-month, county-by-year, day-of-week, and month-by-year fixed effects, as well as flexible weather controls. Standard errors, clustered at the level(s) indicated in each column, are reported in parentheses. Geographic groups are shown in Figure C.2. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Appendix Table C.11. Robustness of IV estimates to additional pollutant controls

	(1)	(2)	(3)	(4)	(5)
PM2.5 ($\mu g/m^3$)	-0.20***	-0.18***	-0.15***	-0.13***	-0.13***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
SO_2 (ppb)		0.009		-0.08	-0.03
		(0.06)		(0.06)	(0.08)
NO_2 (ppb)			-0.07**		-0.03
			(0.03)		(0.04)
O_3 (ppb)				0.12***	0.12***
				(0.01)	(0.01)
First-stage F-statistic	87.36	87.36	87.36	87.36	87.36
R^2	0.86	0.86	0.86	0.86	0.87
Observations	4,495,000	4,495,000	4,495,000	4,495,000	4,495,000
Dependent variable mean	69.85	69.85	69.85	69.85	69.85

Notes: This table reports IV estimates from Equations (4) and (5) with additional pollutant controls. The dependent variable is the number of visits per 1,000 people on the day of exposure. Column (1) presents the baseline specification without additional pollutants. Columns (2)–(5) sequentially add SO_2, NO_2, O_3, or all three pollutants as controls. All pollutants are instrumented using wind direction. Standard errors clustered at the county level are reported in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Appendix Table C.12. Robustness to the COVID-19 pandemic

	(1) Visits (per 1,000 people)	(2) Visits (per 1,000 people)
PM2.5 ($\mu g/m^3$)	-0.20***	-0.25***
	(0.01)	(0.02)
PM2.5 × 1{During COVID}		0.15***
		(0.04)
First-stage F-statistics	87.36	87.36
Dependent variable mean	69.85	69.85
Fixed effects	Yes	Yes
R^2	0.86	0.86
Observations	4,495,000	4,495,000

Notes: This table presents IV estimates from Equations (4) and (5) for different periods. Column (1) reports the baseline results. Column (2) adds an interaction between PM2.5 and an indicator for the COVID-19 period (1{During COVID}), defined as March 15, 2020, to December 10, 2020 (before the FDA issued an emergency use authorization for the COVID-19 vaccine). The dependent variable is the number of visits per 1,000 people on the day of exposure. All regressions include county-by-month, county-by-year, day-of-week, and month-by-year fixed effects, as well as flexible weather controls. Standard errors clustered at the county level are reported in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Appendix Table C.13. Robustness to exclusion of counties without satellite data

	(1) With IDW Visits (per 1,000 people)	(2) Without IDW Visits (per 1,000 people)
PM2.5 ($\mu g/m^3$)	-0.20***	-0.17***
	(0.01)	(0.02)
First-stage F-statistics	87.36	17.86
Dependent variable mean	69.85	66.04
Fixed effects	Yes	Yes R^2
0.86	0.88	
Observations	4,495,000	1,684,900

Notes: This table reports the effect of daily PM2.5 on economic activity using only counties with satellite data. Column (1) presents the baseline specification, where counties without satellite data are interpolated using IDW. The dependent variable is the number of visits per 1,000 people on the day of exposure. All regressions include county-by-month, county-by-year, day-of-week, and month-by-year fixed effects, as well as flexible weather controls. Standard errors clustered at the county level are reported in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.