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AIR QUALITY AND SUICIDE

Claudia Persico
Dave E. Marcotte

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ABSTRACT

We conduct the first-ever large-scale study of the relationship between air pollution and suicide using detailed cause of death data from all death certificates in the U.S. between 2003 and 2010. Using wind direction as an instrument for daily pollution exposure, we find that a 1 g/m3 increase in daily PM2.5 is associated with a 0.49% increase in daily suicides and 0.171 more suicide-related hospitalizations (a 50% increase). Estimates using 2SLS are larger and more robust, suggesting a bias towards zero arising from measurement error. Event study estimates further illustrate that contemporaneous pollution exposure matters more than exposure to pollution in previous weeks.

Claudia Persico
American University
School of Public Affairs
4400 Massachusetts Ave NW
Washington, DC 20016
and IZA
and also NBER
cpersico@american.edu

Dave E. Marcotte
School of Public Affairs
American University
4400 Massachusetts Avenue NW
Washington, DC 20016
marcotte@american.edu

1. Introduction

The evidence establishing air pollution as a health hazard is substantial and expanding. In addition to effects on pulmonary and cardiovascular health, there is growing evidence that air pollution affects the brain and behavior. The effects of air pollution on the brain begin early, altering development *in utero* and during early childhood (Gluckman et al. 2008; Currie, et al. 2014). Pollution can also affect cognitive functioning and decision making because small particulate matter can penetrate the lungs and inhibit the flow of oxygen into the bloodstream and hence the brain (Lavy et al, 2014). Higher levels of air pollution have been linked to lower productivity (Chang et al., 2016, 2019), poorer strategic choices (Künn et al., 2022), and worse performance on academic tests (Heissel, Persico and Simon 2022; Lavy et al., 2014; Marcotte, 2017; Persico and Venator 2021; Zhang et al., 2018).

The effects of air pollution on the brain appear to be more far-reaching than inhibiting functioning and cognition, affecting human-decision making and behavior in other ways (Chen, 2019). For example, there is mounting evidence that higher exposure to contemporaneous air pollution can increase risky behavior including criminal activity (Herrnstadt and Muehlegger 2015) and misbehavior at school (Heissel, Persico and Simon 2019). These effects of pollution on behavior may operate though impacts of exposure on mood. There is evidence that air pollution is negatively associated with self-rated mental health (Zhang et al, 2017; Manczak et al., 2022), and hospitalization for major depression (Kioumourtzoglou et al 2017; Wang et al 2018).

A biological link for this relationship between air pollution and mental health has been identified. Fine particulate matter can greatly increase circulating proinflammatory cytokines that are associated with depressive mood states (Dowlati et al 2010; Gananca et al 2016; Kioumourtzoglou 2017; Janelidze et al 2011; Tonelli et al 2008). Cytokines are a class of proteins involved in neurotransmission and produced by immune cells in response to infection and inflammation (Parkin and Cohen, 2001). Evidence from post-mortem tissue samples has found elevated levels of cytokines in the brains of suicide victims (Tonelli et al., 2008). However, this retrospective association cannot answer whether air pollution and its effects on the body and brain increase prospective risk for suicide. Evidence on this question comes from epidemiological studies of individual cities but is quite limited and mixed. These studies often rely on small or isolated samples or use information on emergency department visits rather than suicide mortality.

Understanding whether air pollution elevates suicide risk is an important question. Suicide rates have been on the rise in the United States (U.S.), having increased by nearly 50% between 2000 and 2019.[1] In 2019, suicide was the tenth leading cause of death, claiming the lives of 47,511 Americans. The study of suicide and how rates vary has been a topic of research in public health and the social sciences for more than a century. Much of this research has been on the impacts of various policies or practices that might reduce suicide rates by restricting access to deadly means, such as firearms (e.g., Ludwig and Cook, 2000; Duggan et al., 2011), toxins (e.g. Kreitman, 1971; Gunnell et al., 2007; Cha et el, 2016), or easy access to high places (Bennewith et al., 2007). A different strand of this research has focused on the roles of social and economic conditions in explaining trends (e.g. Hamermesh and Soss, 1974; Ruhm, 2000 and 2015; Koo and Cox, 2008).[2] Most relevant, there is a large body of research on the effects of psychoactive agents on suicide, including neuropsychiatric medications (Gunnell et al., 2005; Ludwig and Marcotte, 2005; Ludwig et al., 2009) and a growing number of studies on the impact of opioids or other illicit drugs on suicide (e.g., Anderson et al., 2014; Borgshulte et al., 2018).

Despite these growing literatures on the impacts of pollution and behavior, and between psychoactive agents and suicide, the question of how pollution affects suicide is understudied and not well understood. In this paper, we conduct the first-ever large-scale study of pollution and suicide, relying on data for all deaths in the U.S. over eight years. We estimate the impacts of individual pollutants on suicides throughout the U.S. using daily data on suicide counts by state-county matched to daily air quality data from the Center for Disease Control (CDC), daily weather data from the National Oceanic and Atmospheric Administration (NOAA), daily pollution data from the Environmental Protection Agency and CDC, and demographic data between 2003-2010. Using a difference in differences design controlling for weather, population, holidays, day of the week, and county, state-month and month-year fixed effects, we first estimate whether days in the same month, year and county with elevated levels of pollution lead to atypical increases in suicide. We then use variation in wind direction as an instrument for pollution, to limit attenuation bias that results from measuring exposure to pollution within a county-day using fixed monitoring sites. We find that a 1 $\mu g/m^3$ increase in daily Particulate Matter 2.5 (PM2.5), also known as fine particulate

[1] In 2000, age-adjusted suicide rates reached a post-World War II nadir of 10.4 per 100,000 in the U.S. By 2019, suicide rates were 14.5 per 100,000 – the highest yet recorded in the post-war era. (https://www.cdc.gov/nchs/fastats/suicide.htm)

[2] Marcotte and Zejcirovic (2020) provide a recent review of the economic literature on suicide.

matter, is associated with a 0.49 percent increase in daily suicides (a 0.5 percent increase above the mean). In addition, we find that a 1 $\mu g/m^3$ increase in PM2.5 is associated with a 0.3577 percent increase in all daily deaths, which is an increase of 0.4% above the mean. We also find that a 1 $\mu g/m^3$ increase in monthly PM2.5 is associated with 0.171 more suicide-related hospitalizations (a 50% increase above the mean), as well as suggestive evidence that pollution affects self-reported mood more broadly.

In addition to providing the first-ever national study of air pollution and suicide risk in the United States, this paper offers several additional advantages over previous work. First, we use high frequency daily data on air quality from the CDC and the EPA and the number of suicides by county collected by the CDC from all state vital records offices in the United States from 2003 to 2010. While air pollution varies substantially over time, effects on mortality are difficult to identify at the local level because suicide is a rare outcome at the daily level. To provide the first comprehensive study of the link between air pollution and suicide we use daily data over many years for all counties in the U.S. Because most suicide attempts do not result in suicide deaths, we also use data from the Healthcare Cost and Utilization Project's (HCUP) State Inpatient Databases (SID) on suicide-related hospitalizations for the states Arizona, New York, and Washington from 2003 to 2016 and from the CDC's Behavioral Risk Factor Surveillance System (BRFSS), a nationally representative survey of more than 400,000 adults annually at the county level, on self-reported mood.

Second, our study advances the literature on air pollution and suicide by employing the tools of causal inference. We implement the instrumental variables (IV) design of Deryugina et al. (2019) to study overall mortality and health costs of air pollution in the context of a daily county panel that allows us to include a large number of location and time fixed effects. Our high-frequency panel design allows us to estimate effects of pollution on suicide separate from confounding factors that might be associated with suicide in a particular location, year, season, month, and day-of-the-week. By comparing days in the same month in the same county that happen to differ in air quality, we alleviate concerns about time trends in unemployment, poverty, or other seasonal trends in suicide that could affect the results. Our baseline difference-in-differences specification where we compare daily variation in pollution in a county to variation in other counties in the same state over the same time using month-year, state-month, county and day of the week fixed effects, as well as controls for weather, population, unemployment, and holidays. The IV model adapted from Deryugina et al. (2019) builds on this specification by exploiting variation in local air pollution due to daily shifts in wind direction. Our instrumental variables specification limits the impact of measurement error in pollution and reduces any remaining endogeneity concerns by using daily pollution induced by fluctuations in wind direction to provide direct and highly variable dispersal of pollutants over a county's population.

Finally, we estimate the effects of contemporaneous versus chronic pollution exposure using an event study design in which we examine the effects of air pollution leading up to and contemporaneous to each county/week in our data. This sheds light on the temporal mechanisms through which air pollution could lead to suicide.

Our data include high frequency measures of pollution and all deaths in every county in the U.S. over nearly a decade, enabling us also to examine whether the relationship between pollution and suicide varies by the type of pollution, context of exposure, and demographic characteristics of the exposed. First, we investigate what specific types of pollution, such as PM2.5, PM10, nitrogen oxides (NOx), ozone, and sulfur dioxide (SO2) are most likely to increase suicidality. We also investigate whether more rural, poor, unemployed, or polluted counties see the biggest increase in pollution-related suicide deaths by investigating the results by county-level population, pollution level, poverty and employment. We find that intertemporal variation in pollution exacerbates suicide risk most in counties with already higher than normal pollution levels, more rural counties, and in relatively poor counties. One explanation for these patterns is that additional exposure to pollutants causes greater risk in areas with substantial previous exposure or underlying population health risk. This may also explain our finding that impacts are greatest among older age groups.

We also carry out a variety of robustness and falsification checks. We show that our results are not sensitive to our choice of estimator or specification, and to clustering of counties into pollution monitoring groups. As falsification checks, we re-estimate our preferred models replacing the dependent variable with causes of death not known to be affected by pollution and/or pulmonary functioning, and then with causes of death that are affected by pulmonary distress. We find no effects of pollution on mortality from the former, including Lyme disease, metabolic disorders, and digestive diseases, but we find substantial effects from estimating our main specification on causes of death that are known to be affected by pollution, such as chronic obstructive pulmonary disease (COPD) and heart attacks.

While our data do not include information on levels of cytokines or other neurotransmitters through which pollution exposure affects behavior and mood, we attempt to provide some insight into this mechanism in two ways. First, we use the HCUP SID data on monthly suicide-related hospitalizations for the states Arizona, New York, and Washington from 2003 to 2016 matched to pollution and wind data over the same period. We find that a 1 $\mu g/m^3$ increase in PM2.5 leads to 0.171 more suicide-related hospitalizations that month, a 50.5% increase above the mean. We then map our pollution data to responses from the CDC's Behavioral Risk Factor Surveillance System (BRFSS), a large survey of adults at the county level in which respondents are asked about depression and mood. We find evidence that high levels of pollution are associated with a number of measures of depression during the two weeks prior to interview, such as the number of days respondents felt depressed, the number of days respondents reporting little pleasure in doing things, and the likelihood respondents report being told by a healthcare provider that they have a depressive disorder.

2. Background

Air pollution has many effects on human health. Exposure to air pollution increases incidence of both acute and chronic illnesses of the pulmonary system, including upper respiratory infections, asthma, and chronic obstructive pulmonary disease (COPD) (Cascio, 2018). Air pollution has also been shown to have harmful effects beyond the lungs, including increasing risk for cardiovascular disease and mortality (Kampa and Castanas, 2008), and cancer (Straif et al, 2013; Cheng et al, 2020). Whether or how the physiologic effects of air pollution on human health and behavior at the individual level translate into a relationship between air pollution and suicide rates in the community is an open question.

The evidence from the medical literature of the body's cytokine response suggests exposure to air pollution could increase suicide risk though three direct channels. The first is due to air pollution's effects on worsening depression. Major depression has long been linked to elevated risk for suicide attempts and mortality (Malone et al., 1995; Isometsa et al, 1994). The second is by increasing the propensity for risky behavior. For example, substance abuse is among the most important predictors of suicide from an analysis of 28,000 suicide deaths in the U.S. between 2003 and 2008 (Logan et al., 2011). Third, by impacting decision making and the propensity for errors, air pollution may increase the likelihood a suicide attempt is fatal. Most suicide attempts are survived, and economists have modelled attempts as signals (Rosenthal, 1993; Marcotte, 2003). In clinical settings and research on survivors, this is referred to as a "cry for help" (Maple et al., 2020).

While we defer consideration of the empirical importance of these potential mechanisms in our setting until later, we next turn to a review the evidence for these factors generally.

Airborne fine particulate matter can have immediate effects on the functioning of the upper respiratory system by inflaming the bronchial tubes in the lungs and inducing acute asthma attacks. Regular exposure to unhealthy air can lead to chronic problems, including asthma and COPD. Pollutants can also have broader effects on the body, by being absorbed into the vascular system. Some of these effects can lead to harm human health over the long-term. For example, exposure to air pollution has been associated with depression, mood disorders, dementia, and ischemic strokes due to small blood vessel pathology and neuroinflammation (Calderon-Garciduenas et al., 2015a; Calderon-Garciduenas et al., 2015b; Bishop, Ketcham and Kuminoff, 2018).

The broader effects of air pollution on human health are also due to immune response induced by the body's effort to fight of any absorbed particulates. Fine particles trigger the release of antibodies that target them with receptor cells, releasing chemicals to combat the perceived threat. These chemicals include cytokines that cause inflammation of tissue (Janeway et al. 2001). Air pollution has also been implicated in other types of neuroinflammation and neural degradation (Block and Calderon-Gariduenas 2010; Calderon-Gariduenas et al 2015; Bishop, Ketcham and Kuminoff, 2018). In one double-blind randomized crossover study, Chen and colleagues (2018) used true and sham air purifiers to expose healthy young adults in Shanghai to reduced levels of pollution. They find that people exposed to more air pollution have more circulating cytokines and miRNAs that regulate cytokine expression, which are associated with increases in symptoms of depression.

There is substantial evidence in the medical and public health literatures that cytokines affect mood and are linked to major depression (Kronfol and Remick (2000); Dowlati, et al. (2009)). Consequently, in the environmental and public health literatures there has been a growing body of evidence on the relationship between air pollution and cytokines (Chen et al 2018; Kioumourtzoglou et al 2017; Wang et al 2018). Furthermore, cytokines have been linked to depression through the inflammation itself that is induced by exposure to fine particulate matter (Dowlati et al 2010; Gananca et al 2016; Janelidze et al 2011; Tonelli et al 2008). In a recent meta-analysis of 24 studies, Dowlati and colleagues find higher concentrations of proinflammatory cytokines in depressed patients compared with control subjects. Gananca and colleagues recently reviewed the evidence from 22 studies and find that elevated cytokines are also implicated in suicidal ideation, suicide attempts or suicide completion. Janelidze et al (2010) also find evidence that blood cytokine levels might distinguish suicide attempters from depressed patients, where suicidal patients had even more elevated cytokine levels than depressed patients. Kioumourtzoglou and colleagues (2017) also find a direct association between air pollution and the onset of depression. Pun et al (2017) also find a relationship between ambient air pollution and depressive and anxiety symptoms in older adults.

There is also related evidence that suggests higher exposure to contemporaneous air pollution makes people more likely to engage in risky behavior. Heissel, Persico and Simon (2019) find that when elementary or middle school students switch schools from one that is upwind to one that is downwind from a highway in the same neighborhood students are significantly more likely to be suspended from school or absent from school. Similarly, Herrnstadt and Muehlegger (2015) find that people downwind from a highway are more likely to commit crimes than people upwind from the same highway. Persico and Venator (2019) also find that factory openings near schools also increase suspensions and absences from school.

Another strand of research has shown that being exposed to more air pollution also increases the likelihood that people make mistakes. Archsmith, Heyes and Saberian (2018) find that umpires are more likely to make mistakes in calling plays in baseball on days with high pollution. Similarly, Künn et al. (2022) find that chess players are more likely to make mistakes in games on days with higher air pollution, even when playing indoors. Students also score lower on exams on days with higher air pollution, compared with days with lower air pollution (Marcotte 2017; Heissel, Persico and Simon 2019; Du et al., 2022).

While these factors all suggest poor air quality could elevate suicide risk, in a community setting elevated levels of air pollution are often due to human activity that has its own impacts on suicide risk. As the COVID-19 pandemic restricted travel and economic production, air quality improved markedly around the globe, especially in urban areas (Venter et al., 2020; Slezakova and Perreira, 2021). Air pollution due to factory and auto emissions increases with local economic activity and growth. Many empirical studies document a negative relationship between such growth and suicide rates (Koo and Cox, 2008; Reeves et al., 2012; Ruhm, 2000, 2015; see Chen et al. 2012 for an extensive list). Even as pollution may be associated with aggregate economic activity, it may also be positively related to poverty and other suicide risk factors within a city or local area. As Banzhaf and Timmons (2019) review, the economic literature establishing higher risk for exposure to pollutants for the poor and other marginalized persons is robust. So, even as the body's endogenous response to exposure to air pollution may increase suicide risk for the individual, that exposure is associated with contextual factors that also affect suicide risk.

Several recent epidemiological studies of individual cities find mixed evidence on a relationship between suicide and air pollution. Bakian et al (2015) report an association between air pollution and suicide completion in Salt Lake County, Utah. Kim et al (2015) examine six years of data across South Korea and also find an association between air quality and suicide. Szyskowicz et al. find that air pollution increases emergency department visits for suicide attempts in Vancouver. Ng et al. (2016) find effects of air pollution on suicide using data on 29,000 suicide deaths in Tokyo. Using data from Taipei City, Yang et al (2011) also find that suicides follow a seasonal pattern, and that pollution contributes to suicide. However, Fernández-Niño et al. (2018) find no relationship in 4 Columbian cities between air pollution and suicides. In addition, several recent comments by Chen and Samet (2017) and others (e.g., Afshari 2017) urge caution in drawing conclusions from small studies that might suffer from selection bias or other confounding factors. Furthermore, most of these studies use data from outside of the United States, in settings where pollution is often at higher levels.

3. Description of the Data

To advance our understanding of the impact of pollution on suicide in the U.S., we use daily data on deaths by type collected by the CDC from all state vital records offices. We use cause of death data compiled from all death certificates between 2003 and 2010 to calculate daily death rates by suicide (overall and by sex and age groups) in each county in the U.S.[3] Our panel of mortality data is comprehensive and provides detailed information on the universe of deaths over 8 years. So, one big advantage of such a large panel is that our data set does not suffer from selection bias, since it includes all deaths in the United States over this period from suicide and other causes in all 3007 counties in the United States. Using individual death certificates, we generate measures of the number of deaths each day in each county, by cause of death and by demographic characteristics of the deceased. Our unit of analysis is the county/day, and our principal models focus on suicide mortality for all groups.

[3] We use data from this period because we entered into our data use agreement with the CDC in 2012, enabling us to use detailed cause of death data in a secure on-campus location. More recent data are available only in a Restricted Data Center, and COVID has made access difficult.

We also use more recent data from the Healthcare Cost and Utilization Project's (HCUP) State Inpatient Databases (SID) on suicide-related hospitalizations for the states Arizona, New York, and Washington from 2003 to 2016. We aggregate these data to the county-by-month level, since the data only include month and year of hospitalization for our analysis of the effects of pollution on suicide-related hospitalizations.

We match these mortality and hospitalization data to daily data from the EPA and CDC on PM2.5 and other air pollutants. The EPA data include daily data on the Air Quality Index (AQI), which is a scale between 0 and 500 indicating the amount of pollution in the air. Higher scores indicate more air pollution.[4] In addition, we have daily data on the amounts of PM2.5, PM10, ozone, sulfur dioxide, nitrogen dioxide, carbon monoxide and lead in the air, as measured by the EPA's pollution monitors. Finally, we match these data on additional data from the CDC on daily PM2.5, temperature, precipitation and wind speed at the county level and data from NOAA on temperature, precipitation, wind speed, wind direction, and other weather variables. The CDC data includes daily satellite estimates of PM2.5 that were made in a collaboration with NASA. As a result, we have full information for daily PM2.5 for every county in the US from 2003-2010 and thus, do not need to rely on pollution monitor data. This is a strong advantage compared to previous studies that utilize pollution monitor data, since pollution monitors only exist in about 20% of US counties and frequently do not collect data every day. As shown in Panel A of Figure A1, PM2.5 decreases in the first part of the sample period and then increases overall.

Because much of the daily NOAA data is missing wind speed and direction, we also merge in information on daily wind speed and wind direction data from the North American Regional Reanalysis (NARR) data. Wind conditions are reported on a 32 by 32 kilometer grid and consist of vector pairs, one for the east-west wind direction (u-component) and one for the north-south wind direction (v-component). We first locate each wind monitor in a county and then convert the average u- and v-components into wind direction and wind speed and average up to the county-day level. We define "wind direction" as the direction the wind is blowing from.

We match these data to county-level data on demographics and unemployment from the Census and Bureau of Labor Statistics. Suicide rates vary over the business cycle (Ruhm 2000), and as the COVID recession illustrated, pollution increases with human economic activity (Chay and Greenstone 2003). We control for demographic characteristics of a county's population because

[4] The AQI is predominantly determined by Particulate Matter 2.5 (PM2.5) and ozone.

suicide rates vary substantially by race/ethnicity, with suicide rates much higher among non-Hispanic whites than other groups (CDC, 2022). In Table 1, we show the average county characteristics, pollution levels, and suicide rates between 2003-2010 for the counties in our sample, which includes nearly all counties in the United States.

4. Identification Strategy

To estimate the effect of pollution on suicide, we first estimate the relationship between daily variation in pollution levels within a county and suicide rates, net of county fixed effects. Relying on within-county variation in pollution and suicide is vital to limit threats to validity from the contextual factors affecting suicide, described above. For example, suicide can vary by place because of underlying economic or cultural factors (such as the availability of firearms). Because suicides vary both seasonally and based on the day of the week (as shown in Figures A1 and A2), we also control for state-month, month-year, county, day-of-the-week, and holiday fixed effects, as well as time varying measures of daily temperature, precipitation, wind speed, unemployment, and population. So, we estimate the impact of pollution on suicide by comparing changes in suicide within a county as pollution changes at the daily level, net of changes in suicide in other counties in the same county and month-year that saw different changes in pollution. The basic reduced form fixed effects model we use is as follows:

(1) $Y_{idmy} = \beta_1 PM_{idmy} + W_{idmy} + H_{idmy} + \sigma_i + \varphi_d + \gamma_m + \tau_y + \varepsilon_{idmy}$

Y_{idmy} is the log of daily suicides in county i on day of the week d in month m in year y. Because our unit of analysis is at the county/day level, zero is a common outcome. We apply the inverse hyperbolic sine (IHS) transformation to each daily count of suicides to account for zeros in daily suicides: $\text{asinh}(Y_{idmy}) = \log(Y_{idmy} + (Y_{idmy}^2 + 1)^{0.5})$. The IHS transformation is approximately equal to $\log(2(Y_{idmy}))$, except for very small values, and can be interpreted in the same way as a logarithmic transformation (as an approximation of percent change). PM_{idmy} represents various measures of daily pollution in a county. We focus first on the average amount of daily fine particulate matter (PM2.5) in the county, measured in $\mu g/m^3$. W_{idmy} are deciles of daily weather controls for temperature, precipitation, and wind speed and annual controls for county population and the unemployment rate, and H_{idmy} are federal holiday fixed effects. σ_i are county fixed effects, φ_d are day of the week fixed effects, γ_m are state-by-month fixed effects and τ_y are month-by-year fixed effects. We include state-month fixed effects to control for any seasonal correlation between pollution and mental health. In addition, the month-by-year fixed effects should control for common time-varying shocks, such as any broad changes that might affect suicide over our sample period, such as the FDA "black-box" warning on antidepressants in October, 2004.[5] The effect of a 1 μg/m^3 increase in PM2.5 on suicides is given by β_1. Because we use the inverse hyperbolic sine transformation, β_1 is adjusted by β* $\sqrt{1 + \frac{1}{y^2}}$. This is an important adjustment in this context to account for the large number of zeros in the daily suicides data, which results in a low dependent variable mean. Standard errors are clustered at the county level.

While our measures of daily pollution rely on the best available information from locally sited air quality monitors and satellite imaging, measurement error remains a fundamental problem in studies of human exposure to air pollution. This arises because measurements taken at fixed times and locations are inherently imperfect estimates of exposure to a population dispersed over space and active or outdoors at varying times (Gryparis et al., 2009). This introduces a classical measurement error problem that can induce bias into measures of pollution exposure and impact standard errors (Szpiro et al., 2011). To provide some intuition here, imagine a county where the population is evenly dispersed across the county, with a large source of air pollution located in its center. If the wind blows from one direction one day, and the opposite direction another, different residents will be downwind and exposed on different days. In this circumstance, even though exposure for the population could be the same, a single pollution monitor sited on one side of the county would measure high/low levels depending on wind direction. So, the net effect of pollution on health outcomes could be attenuated to zero since a county level measure of pollution would not vary, even if the health of the population exposed is harmed does. County-level aggregate measures of pollution and suicides would simply not measure the variation in within county exposure.

A second problem is that local economic activity could affect suicides in ways other than through pollution. Air pollution is generated from local economic activity, such as factories and power plants, as well as exhaust from vehicles. For example, a major sporting event in a community would raise local PM2.5 by increasing traffic, but it could also raise suicide rates, possibly through loneliness from not being at the event or in response to heavy drinking combined with a favored

[5] In 2004, the FDA issued a black-box warning on antidepressants indicating that they were associated with an increased risk of suicidal thinking and behavior in young people (Friedman 2014).

team's loss.[6] This creates a potential correlation between local economic activity and suicides. The wind instrument addresses this problem because the daily wind direction is uncorrelated with the probability that local economic activity, such as a football game, occurs.

To provide a clearer link between measures of pollution and population exposure, we make use of the fact that while wind can affect the dispersal of pollutants within a county, it also brings air pollution into the county from outside sources. Fine particulate matter (PM2.5) is often carried hundreds of miles by wind (Borgshulte, Molitor and Zou 2020; Deryugina et al 2019), as residents of the east coast of the U.S. learned following the California wildfires of 2021.[7] Since fine PM2.5 from external sources are broadly dispersed and just as harmful to human health as PM2.5 from proximate sources, it creates a threat to an entire county, and hence a clearer link between pollution exposure and population health (EPA, 2003). So, daily wind direction provides an additional exogenous source of within-county variation in pollution levels.

To estimate the impact of exposure to PM2.5 on suicide, we implement an instrumental variables design that uses daily wind direction as an instrument for daily pollution exposure at the county level, controlling for county, state-month, month-year and day of the week fixed effects, as well as temperature, precipitation, wind speed, population, unemployment, and holidays.[8] We cluster pollution monitors into 200 monitor groups and interact these clusters with 4 different bins of wind direction (each being 90 degrees). The specification for our first stage in our two-stage least squares (2SLS) specification is:

(2) $PM2.5_{idmy} = \sum_{g \in G} \sum_{b=0} \beta_b^g \, 1[G_c = g] \; x \; Winddir_{idmy}^{90b} + W_{idmy} + H_{idmy} + \sigma_i + \varphi_d + \gamma_m + \tau_y + \varepsilon_{idmy}$

In equation 2, the instruments are the variables $1[G_c = g] \; x \; Winddir_{idmy}^{90b}$. $Winddir_{idmy}^{90b}$ are a set of binary variables equal to one if the daily average wind direction in county *i* falls within the relevant 90-degree interval [90b, 90b + 90) (and zero otherwise). The omitted category is the interval [270,360). Because we use satellite data for PM2.5 pollution, we use the k-means cluster algorithm to cluster all wind monitors in the United States into 200 spatial groups based on their locations. Figure 1 shows counties assigned to each monitor group. $1[G_c = g]$ is a set of binary

[6] There is good evidence that upset losses of the local professional football team (American and soccer) results in higher levels of alcohol abuse and domestic violence (Card and Dahl, 2011; Ivandic et al., 2021).
[7] See, for example, https://www.nytimes.com/interactive/2021/07/21/climate/wildfire-smoke-map.html
[8] A similar identification strategy was used by Deryugina et al (2019) to estimate the effects of PM2.5 on all-cause mortality.

variables indicating that county *i* is assigned to monitor group *g* from the set of monitor groups *G*. Therefore, our coefficient of interest, β_b^g, is allowed to vary across geographic regions. The other control variables and fixed effects are the same as in equation (1).

Figure 2 depicts our first stage visually using two county groups: the San Francisco Bay Area and Boston. When the wind blows from directions where there is more heavy industry (such as southeast of San Francisco and northeast of Boston), pollution increases. Similarly, Appendix Table A1 shows the coefficients of each of the dummy variables for wind direction interacted with pollution clusters in our first stage. Our first stage is very strong, with an F statistic of 17057.

To provide additional insight into the relationship between pollution and suicide, we assess the relative importance of chronic versus contemporaneous exposure using an event study design that uses weekly averages of pollution in the weeks leading up to a reference day (within a state-county and within a month and year). The advantage of this event study is that it provides non-parametric estimates of mortality effects since the medical literature provides no clear guidance about the timing of biological sequalae of exposure to air pollution. Our event study estimation is given by:

(3) $Y_{idmy} = \beta_0 + \sum_{j=-4}^{0} \beta_j \, \mathbb{1}[\tau_{it} = j]_{st} + W_{idmy} + H_{idmy} + \sigma_i + \varphi_d + \gamma_m + \tau_y + \varepsilon_{idmy}$

β_j is the estimate of the effect of the weekly average air pollution, measured by average AQI in each of the weeks leading up to and following a suicide. We include 4 weeks of lags of air pollution in addition to estimating the effects of pollution on the week of the suicide (in week 0). The models also include county, day of the week, month and year fixed effects, as well as controls for weather, population, unemployment and holidays.[9]

5. Results

5.1. Results on Deaths by Suicide

In Panel A of Table 2 we show results from our reduced form OLS regressions of pollution on the log of suicide deaths, the suicide rate, and deaths from all causes at the daily level in all counties in the U.S. As specified in Equation 1, these models control for local unemployment, population, weather, holidays, county, state-month, month-year, and day of the week fixed effects.

[9] While this specification does not utilize IV, using the number of times the wind blows from the polluted direction in previous weeks as an IV yields similar results.

In Panel A, we find that a daily 1 μg/m^3 increase in PM2.5 is associated with no significant change in suicide deaths, but a 0.0545 percent increase in deaths from all causes.

In Panel B of Table 2, we present results from our primary specification, the 2SLS model that uses daily wind direction as an instrument for daily pollution exposure. We find that a 1 μg/m^3 increase in PM2.5 leads to a 0.4914 percent increase in daily suicides and a 0.4038 percent increase in the daily suicide rate per million individuals. This translates to a 0.5 percent increase in daily suicides above the mean. In addition, we find that a 1 μg/m^3 increase in PM2.5 is associated with a 0.3577 percent increase in all deaths, which is an increase of 0.4% above the mean. For context, 2% of the increase in all deaths caused by air pollution were caused by suicides over this period. Compared to the OLS estimates, the IV estimates are larger, more positive and statistically significant. This is consistent with measurement error creating attenuation bias in our estimates for the reasons we discussed above.

The relative importance of contemporaneous pollution is corroborated by our event study results, presented in Figure 3 showing the effects of pollution in the weeks leading up to, compared to pollution on the week we measure suicide mortality. As is clear in Figure 3, only pollution in the preceding week has a statistically significant effect on the daily suicide rate. While we estimate that pollution two, three and four weeks prior to the reference week are associated with slightly higher than normal suicide rates, they are not statistically significant at conventional levels. This suggests that the impact of air pollution on suicided is due to contemporaneous exposure. This is consistent with previous evidence that pollution could affect suicides by worsening a person's depression and decision-making skills.

5.2. Results on Suicide-related Hospitalizations and Depressive Symptoms

While our analyses provide a clear link between air pollution and suicide mortality, our data provide little opportunity to test the mechanism that motivates our work. As we have described, clinical studies relying on post-mortem tissue samples have linked air pollution to inflammation and production of cytokines, neurotransmitters known to be important in depression and suicide (e.g. Tonelli et al., 2008). Unfortunately, our mortality data come directly from death certificates, and provide no information on the neurobiology or mental health of those who die by suicide. So, we can say nothing about the impact of daily variation in exposure to air pollution on the proximate cause for suicide mortality.

However, we can assess whether the relationship we identify on suicide mortality is due to a broader effect of air pollution on mental health and suicide attempts. Using survey and mortality data, we estimate that approximately one in 30 suicide attempts are fatal.[10] However, most suicide attempts result in trips to a hospital emergency room.[11] To assess whether air pollution has broad effects on suicidal behavior, and suicide mortality is operating through mental health and suicide attempts, we use the data from the HCUP's State Inpatient Databases (SID) for the states Arizona, New York, and Washington from 2003 to 2016. We aggregate suicide-related hospitalizations at the county-by-month level since the data only provides information on the month, location and year of the suicide-related hospitalization. We then use the number of days in the month and prior month the wind blew from the polluted direction as an instrument for average monthly PM2.5 to estimate the relationship between monthly PM2.5 and monthly suicide attempts. Our estimation is given by the following 2SLS equations:

(4) $PM2.5_{\,idmy} = \sum DaysBlewPolluted_{imy} + \sum LastMonthDaysBlewPolluted_{imy} + W_{imy} + \sigma_i + \gamma_m + \tau_y + \varepsilon_{imy}$

(5) $Y_{imy} = \beta_1 \widehat{PM2.5}_{imy} + W_{imy} + \sigma_i + \gamma_m + \tau_y + \varepsilon_{imy}$

Y_{imy} is the number of monthly suicide attempts requiring hospitalization in county i in month m in year y. $PM2.5_{imy}$ represents measures of monthly pollution in a county. $\sum DaysBlewPolluted_{imy}$ represents the number of days the wind blew from the polluted direction in county i. Because some suicides might occur at the beginning of the month, we also instrument for pollution using the number of days in the previous month the wind blew from the polluted direction, represented by $\sum LastMonthDaysBlewPolluted_{imy}$. W_{imy} are monthly weather controls for temperature, precipitation and wind speed and annual controls for county population and the unemployment rate. σ_i are county fixed effects, γ_m are month fixed effects and τ_y are year fixed effects. We include month fixed effects to control for any seasonal correlation between

[10] Estimates of the proportion of the number of Americans who have attempted suicide in a year come from surveys like the National Survey of Drug Use and Health - just under 0.5 percent of adult respondents reported attempting suicide in 2019, which is about 1.4 million persons (https://www.samhsa.gov/data/release/2019-national-survey-drug-use-and-health-nsduh-releases) . Our estimate from CDC mortality data is that 46,145 persons died by suicide in 2019.

[11] In 2017, 64.4% of emergency department (ED) visits related to suicidal ideation or suicide attempt resulted in admission to the hospital, compared to 17.1% for all other ED visits (Owens et al 2020).

pollution and mental health, as well as year fixed effects to absorb any time-varying shocks. The effect of a 1 μg/m^3 increase in monthly PM2.5 on suicide attempts is given by β_1.

Our results, presented in Panel A of Table 3, show that a 1 μg/m^3 increase in monthly PM2.5 is associated with 0.171 more suicide-related hospitalizations that month. This represents a 50.5% increase above the mean in monthly suicide-related hospitalizations. We also estimate the effects of having a month in which the average AQI is above 60 on suicide attempts and find that having a month in which the average AQI exceeds 60 is associated with 4.7 additional suicide-related hospitalizations in that month.

To understand whether pollution affects mood more generally, we also conduct supplementary analyses with data from the CDC's Behavioral Risk Factor Surveillance System (BRFSS), a nationally representative survey of more than 400,000 adults annually at the county level. The surveys include questions on: 1) The number of days respondents felt down, depressed or hopeless in the last two weeks, 2) Reported being told by a healthcare provider they have a depressive disorder, 3) Reported little pleasure in doing things in the last two weeks, and 4) Had little energy or felt tired in the past two weeks. We merge the BRFSS data with our data on pollution and weather by county and interview date. Because our results are driven primarily by high air pollution days, we regress these self-reported mental health outcomes on a continuous variable for the number of days with AQI above 100 in the previous month, controlling for weather, unemployment, population, and county, month and year fixed effects.

We present results of the relationship between air pollution and BRFSS respondents' self-reported mood in Panel B of Table 3. We find that one additional day with an AQI above 100 in a month is associated with a number of measures of depression during the two weeks prior to interview. These include a 2% increase in the number of days respondents felt depressed (column 1); a 1% increase in the number of days respondents reporting little pleasure in doing things (column 3); and a 1% increase in the number of days respondents reporting they had little energy (column 4). We also find that an additional day with AQI above 100 in a month is associated with an increase of 0.2 percentage points in the likelihood respondents report being told by a healthcare provider that they have a depressive disorder – an increase of 1.1% compared to the mean. Self-reported diagnoses and mood states are well-validated measures of clinical depression (e.g. Maske, et al., 2016). Our results in Table 3 make clear that local increases in ambient air pollution are associated with higher levels of depression in the population. While we cannot know the mental health of those who died by suicide from our vital statistics data, the association of air pollution to a major risk factor for suicide and attempted suicides suggests mood states may be an important mechanism of action.

5.3. Heterogeneity in Effects of Pollution

Next, we assess whether the effects of pollution on suicide mortality depend on the type of pollution and affect demographic groups differently. In Table 4, we present results in which we include other pollutants in the same model, allowing wind to instrument for different types of pollution conditional on the other pollutants. Indeed, sulfur dioxide (SO2) and nitrogen dioxide (NO2) are precursors to PM2.5 and can also affect a variety of health outcomes. However, the majority of SO2 and NO2 converts to particulate matter within 2-3 days, so it is difficult to distinguish their independent effects from those of PM2.5. In addition, because data on other pollutants is limited, this decreases the number of observations available to estimate these effects.

The results for PM2.5 are even stronger when conditioning on other pollutants, suggesting that the effects on suicide are likely caused by PM2.5 and not other pollutants. The coefficients on ozone and carbon monoxide are negative, which reflects the finding that ozone is negatively correlated with other pollutants that affect mortality (Currie and Neidell 2005; Deryugina et al 2019).

Since residential segregation, economic and biological factors might increase risk for some groups, we next examine the results by race and gender in Table 5. While the effects of pollution are only statistically significant for Whites, this may be because we have more power to detect effects for Whites since their rates of suicide and daily variation are higher. It is worth noting that the point estimates for Black decedents are nearly 40% larger, although they are not statistically significant at conventional levels. This finding reflects a literature showing that Black individuals are more likely to be exposed to higher amounts of air pollution, which implies a potentially larger effect on mortality (Banzhaf and Timmons 2019; Currie, Voorheis and Walker 2020). In addition, we find statistically significant effects for males, though the point estimates for females are similar in magnitude. Again, we have more statistical power to detect effects for men than for women, since male suicide rates are higher.

Next, we investigate whether suicides vary based on county-level characteristics. Using the National Center for Health Statistics' (NCHS) urban-rural classification scheme, we break counties into urban and rural categories[12] and estimate the effects of pollution on these counties in Columns 5 and 6 of Table 4. The point estimates for rural counties are 23% larger and reach statistical significance, suggesting that pollution might disproportionately affect these counties. Columns 7 and 8 show that the effects of pollution on suicide are worse in counties with above median unemployment and Columns 9 and 10 show that effects are also worse in counties with above-median poverty levels. Columns 11 and 12 suggest that the effects of pollution are worse in counties with above-median pollution levels. This is likely because these counties are more likely to have very high days of pollution more frequently. Because owning a gun also is associated with a much higher likelihood of suicide fatalities (Miller et al 2013), we also categorized states as having more or less restrictive gun laws according to the Gifford's Annual Gun Law Scorecards (2022). As shown in Columns 13 and 14, states with less restrictive gun laws had much larger effects of pollution on suicides.

Because suicide risk and time spent outdoors varies by age, in Table 6 we present the results by age group. The results are largest for people over 55 years of age, suggesting that older individuals might be most harmed by high air pollution days. A 1 $\mu g/m^3$ increase in PM2.5 leads to a 0.775 percent increase in daily suicides for people aged 55-75, and a 0.965 percent increase for people over 75. This corresponds to a literature showing that the elderly are more susceptible to health shocks from pollution, such as dementia and mortality (Bishop, Ketcham and Kuminoff, 2018; Deryugina et al 2019). People aged 15-34 also show an increase in suicides from increased PM2.5, though the results are only significant at the $p<0.1$ level. One potential explanation for this is that younger people are more likely to be exposed to higher levels of pollution because they are more active out of doors. Giaccherini, Kopinska and Palma (2016) similarly find that people between the ages of 15-24 are more likely to have hospitalizations for pollution related causes, such as asthma, because of greater exposure to outdoor pollution.

5.4. Additional Threats to Internal Validity and Other Outcomes

One way we can assess whether our results are driven by increases in air pollution, is to assess whether the dose-response relationship is consistent with the treatment effect identified in Table 2. If pollution is affecting suicide risk, we would expect people exposed to higher levels of

[12] Urban counties are those who are designated a large central metro, large fringe metro or medium metro county by the NCHS. Rural counties are those who are designated a small metro, micropolitan or noncore county.

pollution to have higher mortality. To assess this, we estimate models in which we compared mortality in county/days when PM2.5 AQI is in the range of 25-49, 50-99, and over 100, compared to days when AQI is less than 25. These groups accord with EPA air quality levels of "Good" (< 50) "Moderate" (50-99) and "Unhealthy" (>100). We present the results in Figure 4. The coefficients for air pollution days of less than 100 AQI is close to zero. However, as the AQI increases to 100 or more, daily suicides also increase. Overall, this suggests that our main effects are primarily driven by very high air pollution days.

In order to interpret our main IV results as local average treatment effects (LATE), exposure to pollution for persons living near a monitoring station must increase monotonically with changes in wind direction: Exposure to pollution must increase (or at least never decrease) when the wind blows from the direction of a pollution source. As Deryugina et al. (2019) make clear, the practical implication in our setting is that all counties within a pollution monitoring group should see pollution increase (or decrease) when the wind blows from the same direction. For example, all counties in the same monitoring group in the San Francisco Bay area would need to see air quality diminish when the wind blows from the direction (SE) of the Central Valley. If some counties in the same pollution monitoring cluster experienced diminished air quality while others saw improvements when the wind blew from the same direction, this would violate the monotonicity assumption here.

Deryugina et al. (2019) implement a straightforward test of this assumption that we adopt here. Our IV estimates are weighted up averages of the impacts of changes in wind direction on pollution exposure as measured by coefficients on 4 directional quadrants in 200 monitoring groups. To investigate the validity of the monotonicity assumption inherent in our IV models, a first order test is to change the aggregation of counties into larger or smaller monitoring clusters. This changes the assignment of marginal counties from one cluster to another. Because it allows for variation in the direction of exposure for individual counties, if the assignment of counties to smaller (or larger) clusters changes the IV estimates, this calls the monotonicity assumption into question. In Table 7 we show results using 100 monitor groups, 200 monitor groups or 400 monitor groups. In all cases, our point estimates are quite similar to our main specification. So, the number of monitor groups (and any potential monotonicity violations) has little effect on our estimates and suggests our estimates can be interpreted as a local average treatment effect (LATE).

A remaining concern is whether the wind instrument only affects our outcomes through pollution and not anything else that could be correlated with daily wind direction. To test this, we estimate a series of regressions on placebo causes of death that we would not expect to be affected by pollution. Table 8 presents the results of this placebo analysis. Columns 1 through 5 in Panel A show the results of our main specification on deaths from Lyme disease, congenital anomalies, hernias, metabolic disorders, opioids, and digestive diseases. None of the estimates are statistically significant at conventional levels, and all are near zero.

However, in Panel B in Columns 6-7 of Table 8, we show results from estimating our main specification on causes of death that are known to be affected by pollution: chronic obstructive pulmonary disease (COPD) and ischemic heart attack. As expected, we find larger and statistically significant point estimates for diabetes, COPD and ischemic heart attack, which are consistent with the economics and public health literature. A 1 $\mu g/m^3$ increase in PM2.5 is associated with a 0.331 percent increase in daily COPD deaths, and a 0.295 percent increase in daily heart attack deaths.

In Table 9, we present results from a variety of alternative specifications. One lingering concern is that there are many counties in which suicides are rare, with zero suicides on nearly all days of the year. To assess the sensitivity of our findings to the inclusion of small counties where suicide is a rare event, in column 1 of Table 9, we limit our sample to counties with more than 10,000 people. Similarly, in Column 2, we limit the sample to places that ever had more than one suicide in a day. In both cases, limiting to more populous places increases the size of our coefficient. Indeed, when we population-weight our estimates in column 3, the results increase in magnitude – a 1 $\mu g/m^3$ increase in PM2.5 is associated with a 2.3% increase in daily suicides. Next, we address potential day of the month effects, which might occur if suicide risk changes over the month, perhaps because of timing of payments from work or social or health benefit programs. In Column 4 of Table 9, we add day-month-year fixed effects to our main instrumental variables specification (that also contains state-month, holiday and day of the week fixed effects) and find slightly larger results. In Column 5, we instead add county-year fixed effects to address potential time-varying shocks to counties and find similar results.

To assess whether our results are sensitive to using OLS for an outcome variable with many zeros, we estimate our main IV specification using a Poisson regression by pseudo maximum likelihood (PPML) count model of daily suicides, conditional on the total population by county in

Column 6 of Table 9.[13] Reassuringly, the coefficient using PPML is very similar to that in our primary specification in Table 2, suggesting that our choice of estimator does not drive our results.

Because weather could also affect mood, Column 7 shows the results controlling for 5 levels of cloud cover. While the magnitude of the estimate is somewhat smaller (likely because some cloud cover-related haze is correlated with high air pollution days), it is still statistically significant. Column 8 similarly shows the results when interacting decile bins of temperature and precipitation to ensure that weather interactions do not drive our effects.

Because deaths from suicide might occur with some lag, we also estimate a three-day measure of suicides in Table A2, based on day d and the following 2 days. Thus, a three-day measure nets out short-term mortality displacements onto subsequent days. To ensure that weather does not drive the results, we also control for two leads of our weather variables and two leads of our instruments. We also include seven-day model, which is similarly based on day d and the following 6 days. Our three-day results are somewhat smaller in magnitude than our one-day results, suggesting that there is a small suicide mortality lag from pollution, but that contemporaneous pollution is most closely linked to elevated suicide risk. In addition, the seven-day model is somewhat smaller. This also suggests that there could be some short-term mortality displacement. Nevertheless, the relative importance of contemporaneous pollution is corroborated by our event study results, presented in Figure 3 showing the effects of pollution in the weeks leading up to, compared to pollution on the week we measure suicide mortality.

We also address the concern that data on daily suicides in a county could suffer from serial correlation by showing our main results using weekly estimates of the effects of PM2.5 on suicide deaths in Column 9. Like equations 4 and 5, we use the number of days the wind blows from the polluted direction in a county in a week as an instrument for weekly PM2.5 to estimate the effects of PM2.5 on weekly suicides. We find that a 1 μg/m^3 increase in PM2.5 is associated with a 0.9% increase in weekly suicides. Column 9 of Table 9 shows the effects of PM2.5 on weekly suicides are larger than the daily effects, suggesting that there could be cumulative effects from pollution exposure, and that the results are not solely due to short-term mortality displacement.

[13] In this specification we bootstrap our standard errors 500 times.

Because satellite-derived pollution data might have measurement error for daily analysis, Panel B of Table A2 replicates our main findings using pollution monitor data only. The estimates are similar to those in Table A2.

6. Conclusion

This is the first study showing that air pollution increases suicides. Using daily wind direction as an instrument for daily fine particulate matter exposure, we find that a 1 μg/m^3 increase in PM2.5 leads to a 0.49 percent increase in the daily suicide rate. We further find that our results are primarily driven by contemporaneous exposure to air pollution, and that days of very high air pollution appear to drive the effects on suicides. We also find that increased PM2.5 increases the likelihood of all deaths on days of high air pollution, as well as deaths from COPD and ischemic heart attack. In addition, we find that increases in PM2.5 increase the number of monthly suicide-related hospitalizations and result in more self-reported depressive symptoms.

In our preferred instrumental variables model, we find that a 1 μg/m^3 increase in PM2.5 leads to a 0.49 percent increase in daily suicides and a 0.4 percent increase in the daily suicide rate per million individuals. These results imply that on a day with PM2.5 at the threshold of unhealthy levels (35 μg/m^3), the average county would experience an increase in daily suicides about 0.094 per million population average air quality compared to a day with average PM2.5 levels (11.6 μg/m^3). [14] This is a small number, but it is a daily risk. So, in a county with a million residents, a year with 11 additional unhealthy air days would see 1 additional suicide death.

To further quantify the number of additional deaths that occur due to air pollution over this time period, we attempt a back of the envelope calculation for the effect of a 1 μg/m^3 increase in PM2.5 over this time period on suicide deaths. We find that a 1 μg/m^3 increase in PM2.5 on each day over a year would lead to 153.8 additional suicides in that year.[15] The average amount air pollution increases (or decreases) from day to day within a county is about 4 μg/m^3. Nevertheless, it is important to note that daily air pollution is highly variable in the U.S., and there are both

[14] A linear extrapolation of the 0.004038 increase per million residents due to a 1 μg/m^3 to the 23.4 μg/m^3 difference between 35 and the mean implies and increase of 0.094 per million.

[15] On average, there were 31,296.88 suicides per year between 2003-2010, or about 85.75 suicides per day. Using the 0.004914 percent increase, this suggests that there would be 0.4214 additional suicides per day from a 1 μg/m^3 increase in PM2.5 on average. Multiplied by 356 days in the year gives us 153.8 additional suicides per year.

increases and decreases over time in average annual amounts of PM2.5 during our study period (as shown in Figure A1).

This work contributes to our understanding of the social determinants of health as well as how environmental policy relates to social policy. Our findings provide evidence relevant for understanding the full costs of air pollution on human health and mortality – along with some potential avenues for protection and prevention. The World Health Organization estimated that ambient air pollution resulted in an additional 77,550 deaths in the U.S. in 2016 due to cardiovascular and pulmonary diseases (WHO, 2022). Our work makes clear that this figure understates the effect of ambient air pollution on mortality. The U.S. Environmental Protection Agency currently values a human life at $10.4 million.[16] Our estimates of suicide mortality attributable to air pollution implies a cost of $1.6 billion annually in terms of air pollution's effect on suicide alone for a 1 μg/m3 increase in daily PM2.5. Consequently, any analyses of policies intended to limit pollution need to reflect these more expansive estimates of the full effect exposure on human health.

In addition to clarifying the true costs of pollution, this research contributes to our understanding of the environmental processes that impact suicidality. Most directly, it is important for physicians and those who have persons at risk in their families to recognize that air quality can play a role in mood and mortality. In the public health world, efforts to temporarily take guns from the suicidal appear to be protective (e.g., Kivisto and Phalen, 2018). Because air pollution is a risk, interventions to keep those at risk of suicide indoors or refrain from strenuous activity outdoors are likely to provide protection. In settings with high numbers of persons at risk, such as in-patient mental health treatment facilities, air filtration and purifying systems could be protective for depressed patients on high air pollution days.

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Tables

Table 1: Descriptive Statistics of Counties in the Sample

	(1) Characteristics of Counties in the U.S. from 2003-2010
Total Population	95,615
	[311,963]
Percent White	0.841
	[0.159]
Percent Black	0.108
	[0.133]
Percent Hispanic	0.197
	[0.246]
Percent Poverty	0.152
	[0.058]
Median Income	40,590
	[9,778]
Unemployment Rate	0.063
	[0.02]
Average Total Deaths by Suicide by County-Day	0.0303
	[.1939]
Average Daily Suicide Rate	0.378
	[0.188]
Average Daily PM2.5 Concentration	11.63
	[2.04]
Number of Counties	2,835
Number of County-day observations	8,262,736

Notes: This table shows the average characteristics of counties in our main sample with standard deviations in brackets below each mean. Column 1 shows characteristics of all counties in the United States between 2003-2010

Table 2: Effects of PM2.5 on Suicides and All Deaths using state-month, month-year, county, and day of the week FEs

	(1) Log of daily suicides (1 day model)	(2) Log of daily suicide rate (1 day model)	(3) Daily Suicides (levels)	(4) Log of All Deaths
	Panel A: OLS Estimates			
Average daily PM 2.5, $\mu g/m^3$	-0.000461	-0.000063	-0.000011	0.000545***
	(0.000367)	(0.000078)	(0.000011)	(0.000059)
	Panel B: IV Estimates			
Average daily PM 2.5, $\mu g/m^3$	0.004914***	0.004038**	0.000146***	0.003577***
	(0.001675)	(0.001902)	(0.000052)	(0.000236)
Mean of Outcome	0.0255	0.0623	0.030302	0.7842
F-statistic	17057	17057	17057	14553
Observations	8262736	8262736	8262736	8262736

Notes: This table reports the effect of PM2.5 on suicide deaths and all deaths. Each cell shows the results of a separate regression with standard errors in parenthesis. Column 1 shows estimates for the log of daily suicides and Column 2 shows estimates for the log of the daily suicide rate per million people. Column 3 shows estimates for the number of daily suicides per county and Column 4 shows estimates for the log of all daily deaths. Panel A reports estimates using OLS regression. Panel B reports estimates using wind as an instrument for pollution. Our primary specification uses 200 monitor groups. All regressions control for county, state-month, month-year and day of week fixe effects, holidays, total population, deciles of average temperature, precipitation, and wind speed, and the unemployment rate. Standard errors are clustered at the county level and are in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 3: IV effect of PM2.5 on Monthly Suicide-related Hospitalizations

	(1) Monthly Suicide-related Hospitalizations	(2) Monthly Suicide-related Hospitalizations		
	Panel A: Effect of PM2.5 on Monthly Suicide-related Hospitalizations			
Average Monthly PM 2.5, μg/m³	0.170692**			
	(0.085999)			
Months with Average AQI Above 60		4.699539**		
		(2.371069)		
Mean of Outcome	0.338522	0.338522		
F-Statistic	100	24		
Observations	81243	81243		
	Panel B: The Effects of Daily PM2.5 on Self-Reported Mental Health			
	(3) Number of Days You Felt Depressed in the Last 2 weeks	(4) Were Ever Told by a Healthcare Provider You Have a Depressive Disorder	(5) Number of Days in the Last 2 Weeks You Had Little Pleasure in Doing Things	(6) Number of Days in the Last 2 Weeks You Had Little Energy or Felt Tired
Days with AQI>100/Month	0.020735***	0.001964**	0.011875*	0.025914***
	(0.005815)	(0.000860)	(0.006833)	(0.009649)
Mean of Outcome	1.18	0.18	1.54	3.47
Observations	26496	26446	26310	26412

Notes: Panel A of this table reports the effects of PM2.5 on monthly suicide-related hospitalizations from the HCUP SID. Column 1 shows the effects of a 1 μg/m3 increase in monthly PM2.5 on monthly suicide-related hospitalizations. Column 2 shows the effects of an additional month with AQI above 60 on suicide-related hospitalizations. Panel B of this table reports the effect of the number of days with AQI above 100 on self-reported mood from the BRFSS survey. All regressions control for county, month and year fixed effects, as well as average monthly weather controls, holidays, total population and the unemployment rate. Standard errors are clustered at the county level and are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 4: IV effect of Different Pollutants on log of suicide using state-month, month-year, county, and day of the week FEs

	(1) Log of Suicides
PM2.5	0.077578**
	(0.034646)
SO2	0.050681
	(0.077261)
O3	-0.016548
	(0.029018)
CO	-0.003576*
	(0.001887)
NO2	-0.041641
	(0.055045)
Mean of Outcome	0.2492
F-Statistic	9
Observations	210426

Notes: This table reports the effect of different pollutants on the log of daily suicide deaths. All pollutants are in the same regression with wind as an instrument for pollution. Our primary specification uses 200 monitor groups. Our primary specification uses 200 monitor groups. All regressions control for county, state-month, month-year and day of week fixed effects, holidays, total population, deciles of average temperature, precipitation, and wind speed, and the unemployment rate. Standard errors are clustered at the county level and are in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 5: Heterogeneity by Race, Gender and County-level Characteristics

	Log Suicides					
	Panel A: By Individual Race and Gender				*Panel B: By County-level Characteristics*	
	(1)	(2)	(3)	(4)	(5)	(6)
	White	Black	Female	Male	Urban Counties	Rural Counties
Daily PM 2.5	0.003925**	0.006855	0.00487	0.00458**	0.009040	0.011634**
	(0.001793)	(0.007107)	(0.00364)	(0.00190)	(0.006463)	(0.005389)
Mean of Outcome	0.02338	0.001445	0.00547	0.02041	0.025543	0.025543
F-Statistic	17057	17057	17057	17057	285	285
Observations	8262736	8262736	8262736	8262736	8262736	8262736

Panel B: By County-level Characteristics

	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Below median Unemployment	Above Median Unemployment	Below Median Poverty	Above Median Poverty	Below Median Pollution levels	Above Median Pollution levels	More Restrictive State Gun Laws	Less Restrictive State Gun Laws
Daily PM 2.5	0.004554	0.009144***	0.004258*	0.009447***	0.006577***	0.009564***	0.005383**	0.009074***
	(0.003001)	(0.003333)	(0.002531)	(0.003549)	(0.002443)	(0.003242)	(0.002703)	(0.003288)
Mean of Outcome	0.025543	0.025543	0.025543	0.025543	0.025543	0.025543	0.025543	0.025543
F-Statistic	17875	17875	1032	1032	12837	12837	23537	23537
Observations	8262736	8262736	8262736	8262736	8262736	8262736	8262736	8262736

Notes: This table reports the effect of daily PM2.5 on the log of daily suicide deaths for different groups. Panel A, Columns 1-4 show the results by individual decent characteristics, while Panel B, Columns 5-12 show the results by county characteristics. Column 1 shows the results for Whites, Column 2 shows the results for Blacks, Column 3 shows the results for females, and Column 4 shows the results for males. Columns 5-6 show the results for urban and rural counties, Columns 7-14 show the results for counties with above and below median unemployment, poverty, pollution levels and restrictive state gun laws. Our primary specification uses 200 monitor groups. All regressions control for county, state-month, month-year and day of week fixed effects, holidays, total population, deciles of average temperature, precipitation, and wind speed, and the unemployment rate. Standard errors are clustered at the county level and are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 6: Effect of PM2.5 on Log Suicides by Age

	Log Suicides				
	(1) Age 0-14	(2) Age 15-34	(3) Age 35-54	(4) Age 55-74	(5) Age 75+
Daily PM2.5	-0.00242	0.00517*	0.00174	0.00775**	0.00965*
	(0.02046)	(0.00290)	(0.00262)	(0.00359)	(0.00554)
Mean of Outcome	0.00019	0.00720	0.01082	0.00574	0.00230
F-Statistic	17057	17057	17057	17057	17057
Observations	8262768	8262768	8262768	8262768	8262768

Notes: This table reports the effect of daily PM2.5 on the log of daily suicide deaths for different age groups. Column 1 shows the results for people ages 0-14, Column 2 shows the results for ages 15-24, Column 3 shows the results for ages 25-34, Column 4 shows the results for ages 25-34, etc. Our primary specification uses 200 monitor groups All regressions control for county, state-month, month-year and day of week fixed effects, holidays, total population, deciles of average temperature, precipitation, and wind speed, and the unemployment rate. Standard errors are in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 7: IV effect of PM2.5 on log of suicide using state-month, month-year, county, and day of the week FEs with different numbers of Monitor Groups

	(1)
	Log suicides
	Panel A: 100 Monitor Groups
Average daily PM 2.5, μg/m³	0.004080**
	(0.001641)
F-Statistic	29345
	Panel B: 300 Monitor Groups
Average daily PM 2.5, μg/m³	0.004459***
	(0.001658)
F-Statistic	741
	Panel C: 400 Monitor Groups
Average daily PM 2.5, μg/m³	0.004313**
	(0.001688)
F-Statistic	693
Mean of Outcome	0.025543
Observations	8262736

Notes: This table reports the effect of PM2.5 on the log of daily suicide deaths. Panel A reports estimates using 100 monitor groups. Panel B reports estimates using 300 monitor groups, and Panel C reports estimates using 400 monitor groups. Our primary specification uses 200 monitor groups. All regressions control for county, state-month, month-year and day of week fixed effects, holidays, total population, deciles of average temperature, precipitation, and wind speed, and the unemployment rate. Standard errors are clustered at the county level and are in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 8: Effect of PM2.5 on Placebo deaths and Air Pollution-related Deaths

Panel A Placebo Causes of Death

	(1) Log Deaths from Lyme disease	(2) Log Deaths from Congenital anomalies	(3) Log Deaths from Hernia	(4) Log Deaths from Metabolic Disorder	(5) Log Deaths from Digestive Disease	(6) Log Deaths from Opioids
Daily PM 2.5	-0.01492	0.00341	0.00198	0.00142	0.00256	0.00461
	(0.13661)	(0.00384)	(0.00868)	(0.00291)	(0.00259)	(0.00292)
Mean of Outcome	0.00001	0.00654	0.00115	0.01154	0.01438	0.01090
F-Statistic	17057	17057	17057	17057	17057	17057
Observations	8262736	8262736	8262736	8262736	8262736	8262736

Panel B: Deaths Related to Air Pollution

	(7) Log Deaths from Chronic Obstructive Pulmonary Disease	(8) Log Deaths from Ischemic Heart Attack
Daily PM 2.5	0.00331***	0.00295***
	(0.00087)	(0.00048)
Mean of Outcome	0.08967	0.25277
F-Statistic	17057	17057
Observations	8262736	8262736

Notes: This table reports the effect of daily PM2.5 on the log of different daily causes of death. Each column represents the results from a different regression. Columns 1-5 shows the results for placebo causes of death we would not expect to be impacted by air pollution. Columns 6-8 show results for causes of death that have been shown to be affected by air pollution. Our primary specification uses 200 monitor groups. All regressions control for county, state-month, month-year and day of week fixed effects, holidays, total population, deciles of average temperature, precipitation, and wind speed, and the unemployment rate. Standard errors are in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 9: Results for Alternative Samples and Alternative Specifications

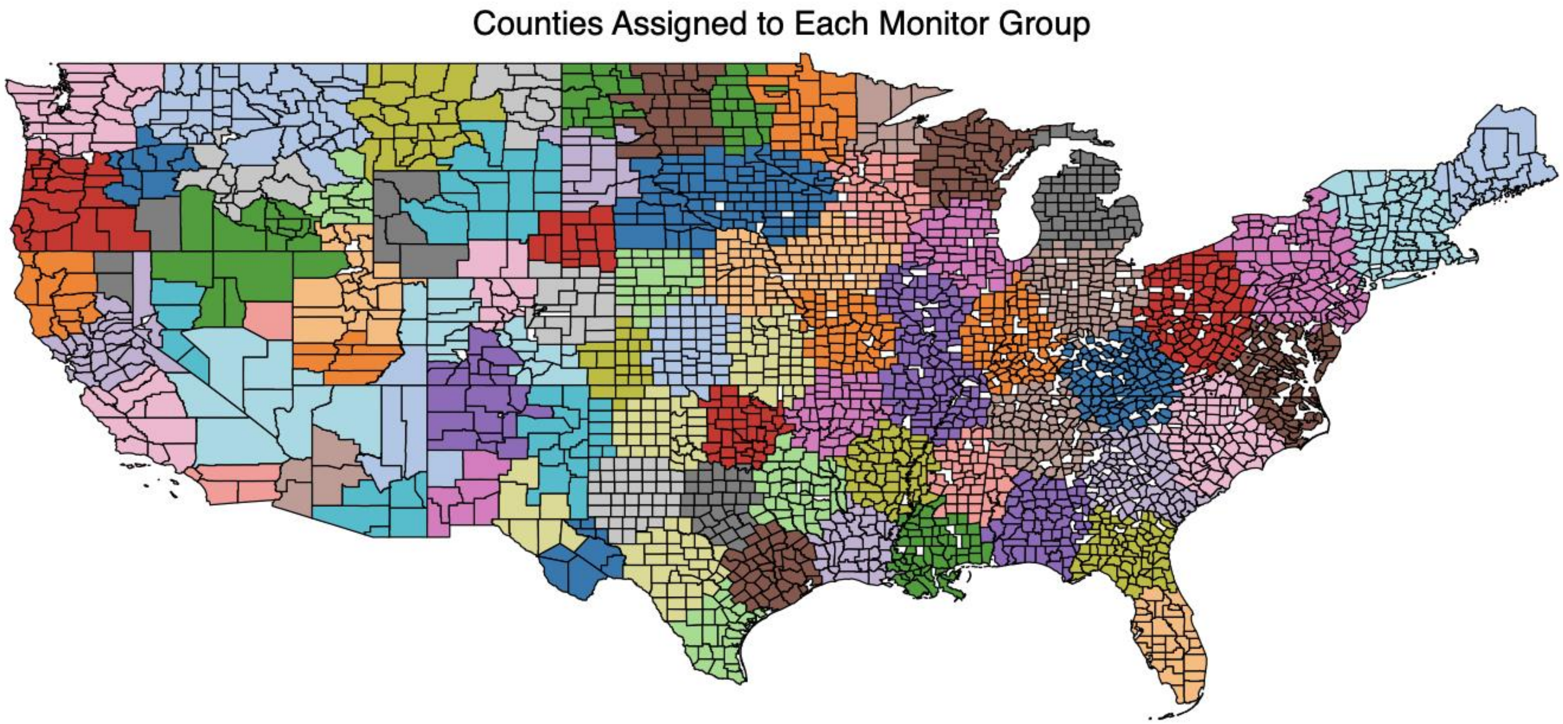
	Log Suicides								
	(1) Limiting to Counties with >10,000 people	(2) Limiting to Counties that ever had 2 or more suicides/ day	(3) Population-weighted estimates	(4) Using Day-Month-Year Fixed Effects	(5) Using County-Year Fixed Effects	(6) Using PPML with IV	(7) Controlling for Cloud Cover	(8) Interacting temperature and precipitation	(7) Weekly Suicides
PM 2.5	0.00585***	0.008233**	0.02255**	0.005525**	0.00484***	0.003870***	0.00234***	0.004930***	0.009139**
	(0.001896)	(0.003630)	(0.00964)	(0.002156)	(0.001673)	(0.001262)	(0.000884)	(0.001678)	(0.003747)
Mean of Outcome	0.031839	0.064045	0.062264	0.025543	0.025543	0.025543	0.025543	0.025543	0.151100
F-Statistic	8659	60868	12510	14553	67131	19360	12449	8986	4387
Observations	6522413	2698046	8262736	8262736	8262736	8182898	8262736	8262736	1178534

Notes: This table reports the effect of PM2.5 on the log of daily suicide deaths. Each column represents the results of a different regression. Column 1 reports estimates when limiting the sample to counties with more than 10,000 people. Column 2 reports estimates when limiting the sample to counties that ever had two or more suicides in a day. Column 3 shows the population-weighted estimates. Columns 4-5 presents the results of our primary specification when adding different fixed effects. Column 6 presents the results when using PPML in the IV rather than OLS. Columns 7-8 control for cloud cover and the interaction of temperature and precipitation. Column 9 shows the aggregated results for weekly suicides. All regressions control for county, state-month, month-year and day of week fixed effects, holidays, total population, deciles of average temperature, precipitation, and wind speed, and the unemployment rate. Standard errors are clustered at the county level and are in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

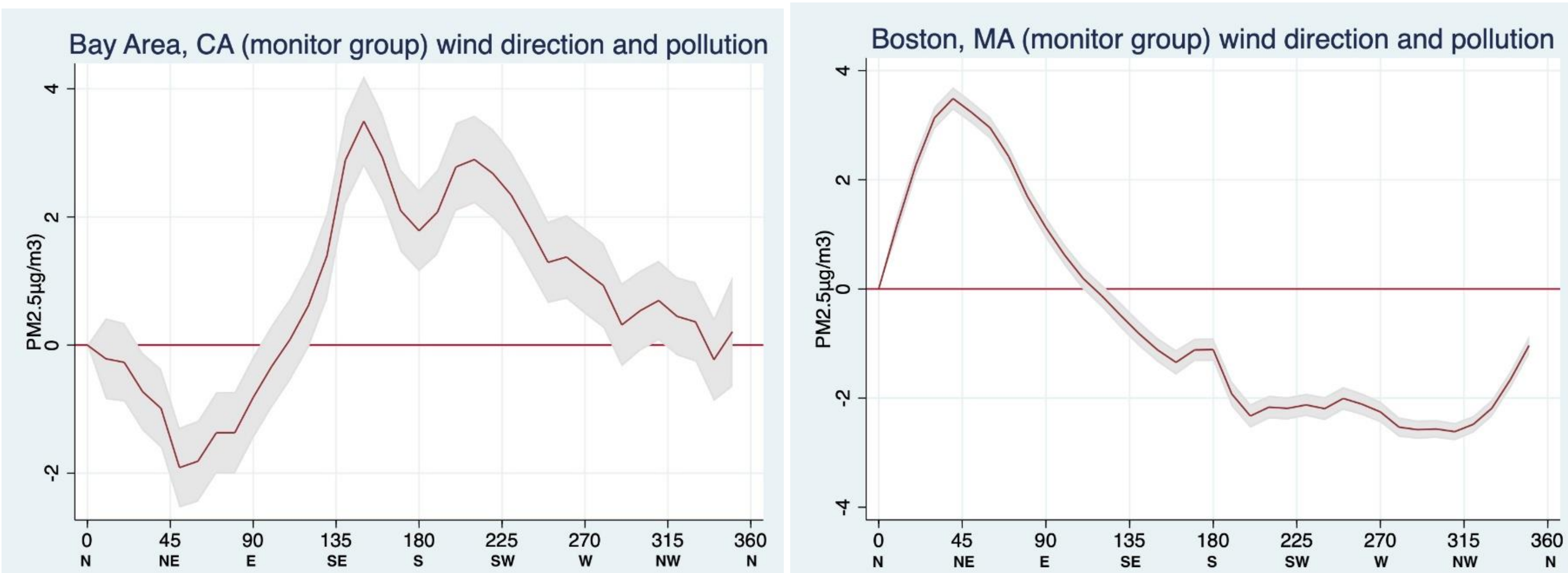
Figures

Figure 1: Counties Assigned to 200 Monitor Groups



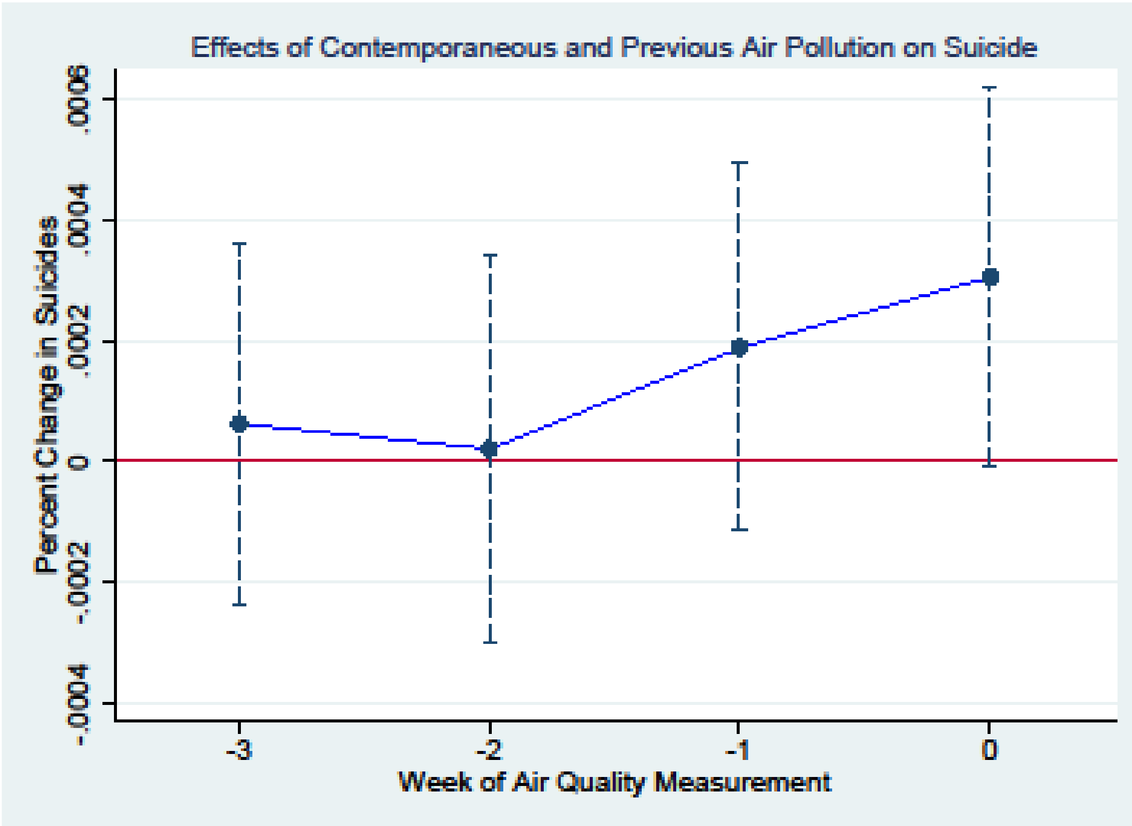
Notes: This figure depicts the 200 monitor groups in our sample, which comprises nearly every county in the entire United States. Counties are assigned to monitor groups using wind monitors and the k-means clustering algorithm.

Figure 2: Examples of wind direction and pollution exposure



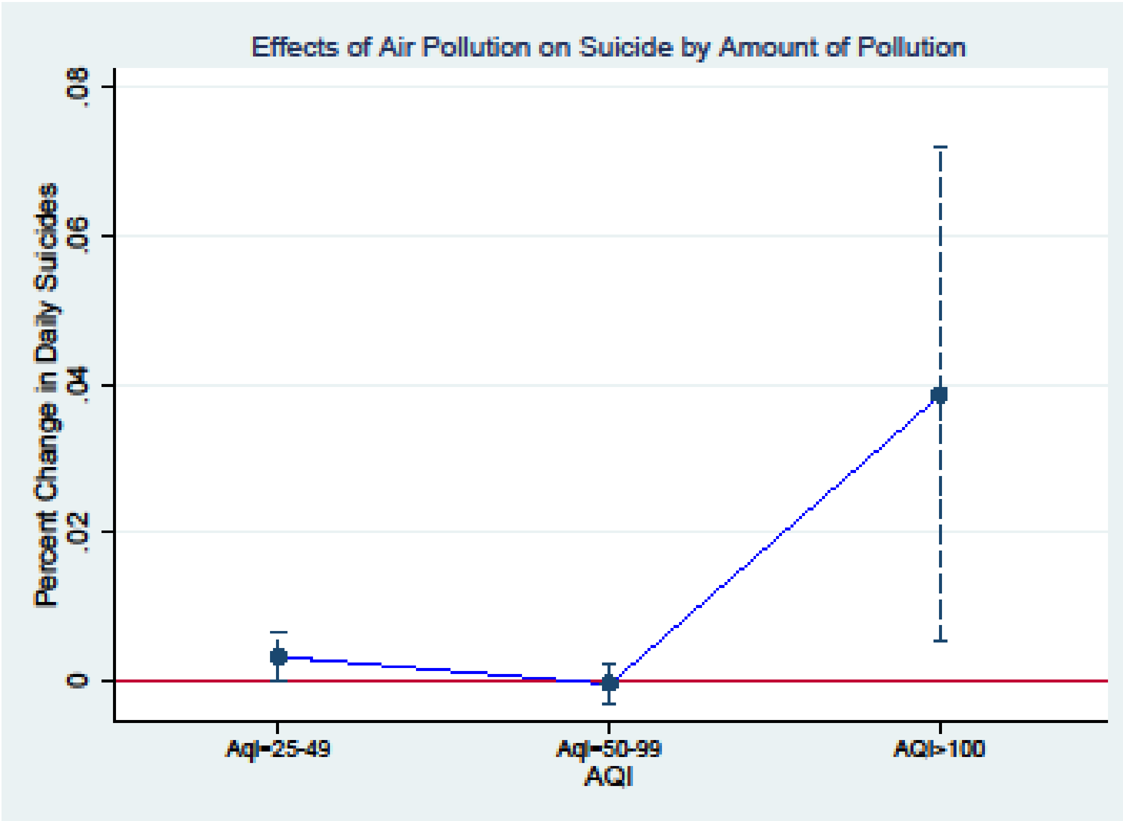
Notes: This figure depicts our first stage in two example monitor groups: the Bay Area and Boston. As shown, in some wind directions, average PM2.5 concentrations increase, and in others, they decrease. 95% confidence intervals depicted in gray.

Figure 3: Effects of Contemporaneous and Previous Air Pollution on Suicide



Notes: This figure depicts an event study of the effect of the log of the weekly AQI on the log of suicides over weeks of exposure. The week labeled 0 is the week leading up to a suicide. We control for holidays, total population, average temperature, average precipitation, wind speed, the unemployment rate, and county, month, year and day of the week fixed effects. 95% confidence intervals are depicted as vertical bars and standard errors are clustered at the county level.

Figure 4: Effect of Air Pollution on Suicide by Amount of Pollution



Notes: This figure plots non-parametric estimates of the effect of different binned amounts of AQI on the log of daily suicides. The omitted category is AQI of less than 25. We control for county, state-month, month-year and day of week fixed effects, holidays, total population, deciles of average temperature, precipitation, and wind speed, and the unemployment rate. Vertical bars represent 95% confidence intervals based on standard errors clustered at the county level.

Online Appendix Tables and Figures

Table A1: First Stage Effects of Daily Wind on Daily Pollution

Binned Wind Direction Interacted with Pollution Clusters	(1) PM25 concentration
Angle range 0-90	0.657462
	(0.418599)
Angle range 90-180	0.121036
	(0.363051)
Angle range 180-270	0.332466
	(0.466601)
1b.poll_cluster#0b.ang_range	0.000000
	(0.000000)
1b.poll_cluster#90.ang_range	-0.682755***
	(0.048382)
1b.poll_cluster#180.ang_range	-0.905897***
	(0.048735)
1b.poll_cluster#270.ang_range	-0.335548***
	(0.010560)
4.poll_cluster#0b.ang_range	3.020103***
	(0.182940)
4.poll_cluster#90.ang_range	1.728198***
	(0.255016)
4.poll_cluster#180.ang_range	-0.993519***
	(0.165117)
4o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
5.poll_cluster#0b.ang_range	1.155568***
	(0.126336)
5.poll_cluster#90.ang_range	2.520459***
	(0.117477)
5.poll_cluster#180.ang_range	1.238717***
	(0.083843)
5o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
6.poll_cluster#0b.ang_range	2.699945***
	(0.110529)
6.poll_cluster#90.ang_range	3.109083***
	(0.118307)
6.poll_cluster#180.ang_range	1.053787***
	(0.126945)
6o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
7.poll_cluster#0b.ang_range	3.361771***
	(0.104123)

7.poll_cluster#90.ang_range	4.922075***
	(0.126225)
7.poll_cluster#180.ang_range	2.304450***
	(0.070106)
7o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
8.poll_cluster#0b.ang_range	-1.832307***
	(0.372914)
8.poll_cluster#90.ang_range	1.438480***
	(0.255817)
8.poll_cluster#180.ang_range	1.507893***
	(0.235089)
8o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
9.poll_cluster#0b.ang_range	-0.242917
	(0.541405)
9.poll_cluster#90.ang_range	0.006974
	(0.577606)
9.poll_cluster#180.ang_range	-0.260134
	(0.491887)
9o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
10.poll_cluster#0b.ang_range	-0.736382***
	(0.078182)
10.poll_cluster#90.ang_range	-1.230279***
	(0.098925)
10.poll_cluster#180.ang_range	0.212761***
	(0.050492)
10o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
11.poll_cluster#0b.ang_range	0.956841***
	(0.140342)
11.poll_cluster#90.ang_range	1.863135***
	(0.189576)
11.poll_cluster#180.ang_range	1.476981***
	(0.102226)
11o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
12.poll_cluster#0b.ang_range	2.096488***
	(0.082981)
12.poll_cluster#90.ang_range	3.767149***
	(0.069101)
12.poll_cluster#180.ang_range	2.327743***
	(0.117717)
12o.poll_cluster#270o.ang_range	0.000000
	(0.000000)

13.poll_cluster#0b.ang_range	-1.256299***
	(0.111901)
13.poll_cluster#90.ang_range	-2.754201***
	(0.104636)
13.poll_cluster#180.ang_range	-1.141604***
	(0.116566)
13o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
14.poll_cluster#0b.ang_range	2.745877***
	(0.194485)
14.poll_cluster#90.ang_range	1.990708***
	(0.227156)
14.poll_cluster#180.ang_range	0.138460
	(0.236928)
14o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
15.poll_cluster#0b.ang_range	1.453112***
	(0.092445)
15.poll_cluster#90.ang_range	2.422154***
	(0.076431)
15.poll_cluster#180.ang_range	1.909814***
	(0.088942)
15o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
16.poll_cluster#0b.ang_range	3.249706***
	(0.077480)
16.poll_cluster#90.ang_range	5.340938***
	(0.077926)
16.poll_cluster#180.ang_range	2.467974***
	(0.082613)
16o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
17.poll_cluster#0b.ang_range	3.593646***
	(0.113365)
17.poll_cluster#90.ang_range	4.410900***
	(0.172290)
17.poll_cluster#180.ang_range	1.939015***
	(0.049776)
17o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
18.poll_cluster#0b.ang_range	0.764797***
	(0.113263)
18.poll_cluster#90.ang_range	-0.125169***
	(0.045309)
18.poll_cluster#180.ang_range	0.604418***
	(0.018825)

18o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
19.poll_cluster#0b.ang_range	1.142773***
	(0.105811)
19.poll_cluster#90.ang_range	2.815342***
	(0.077107)
19.poll_cluster#180.ang_range	2.006965***
	(0.077089)
19o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
21.poll_cluster#0b.ang_range	1.347336***
	(0.145407)
21.poll_cluster#90.ang_range	3.521453***
	(0.150367)
21.poll_cluster#180.ang_range	1.751777***
	(0.123719)
21o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
23.poll_cluster#0b.ang_range	1.894563***
	(0.202822)
23.poll_cluster#90.ang_range	0.970286***
	(0.236397)
23.poll_cluster#180.ang_range	-0.985107***
	(0.188479)
23o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
24.poll_cluster#0b.ang_range	-2.132491***
	(0.618804)
24.poll_cluster#90.ang_range	-1.455090***
	(0.476750)
24.poll_cluster#180.ang_range	0.904114
	(0.838397)
24o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
25.poll_cluster#0b.ang_range	1.833647***
	(0.108304)
25.poll_cluster#90.ang_range	2.946865***
	(0.079254)
25.poll_cluster#180.ang_range	1.843893***
	(0.048859)
25o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
26.poll_cluster#0b.ang_range	2.355590***
	(0.158202)
26.poll_cluster#90.ang_range	3.938911***
	(0.198732)

26.poll_cluster#180.ang_range	1.483046***
	(0.129730)
26o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
27.poll_cluster#0b.ang_range	-0.015083
	(0.150523)
27.poll_cluster#90.ang_range	0.238442
	(0.160452)
27.poll_cluster#180.ang_range	0.400190***
	(0.119360)
27o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
28.poll_cluster#0b.ang_range	0.462410***
	(0.075249)
28.poll_cluster#90.ang_range	2.216258***
	(0.054273)
28.poll_cluster#180.ang_range	0.733836***
	(0.086518)
28o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
29.poll_cluster#0b.ang_range	1.340002***
	(0.086469)
29.poll_cluster#90.ang_range	3.259530***
	(0.110384)
29.poll_cluster#180.ang_range	2.287978***
	(0.064644)
29o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
30.poll_cluster#0b.ang_range	1.718159***
	(0.167431)
30.poll_cluster#90.ang_range	1.863736***
	(0.225606)
30.poll_cluster#180.ang_range	1.184355***
	(0.101730)
30o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
32.poll_cluster#0b.ang_range	1.386950***
	(0.153598)
32.poll_cluster#90.ang_range	3.465375***
	(0.133109)
32.poll_cluster#180.ang_range	1.527326***
	(0.076184)
32o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
34.poll_cluster#0b.ang_range	-0.376033***
	(0.100797)

34.poll_cluster#90.ang_range	-0.032913
	(0.151257)
34.poll_cluster#180.ang_range	0.221907
	(0.194384)
34o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
35.poll_cluster#0b.ang_range	2.276288***
	(0.230541)
35.poll_cluster#90.ang_range	1.726223***
	(0.269944)
35.poll_cluster#180.ang_range	0.714475***
	(0.154119)
35o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
36.poll_cluster#0b.ang_range	2.099476***
	(0.070141)
36.poll_cluster#90.ang_range	4.312308***
	(0.099430)
36.poll_cluster#180.ang_range	2.031376***
	(0.076999)
36o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
38.poll_cluster#0b.ang_range	0.022567
	(0.152984)
38.poll_cluster#90.ang_range	-0.360877
	(0.228700)
38.poll_cluster#180.ang_range	-0.133212
	(0.095903)
38o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
39.poll_cluster#0b.ang_range	4.807981***
	(0.109846)
39.poll_cluster#90.ang_range	3.910265***
	(0.191101)
39.poll_cluster#180.ang_range	0.121878
	(0.222570)
39o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
40.poll_cluster#0b.ang_range	0.579251***
	(0.190808)
40.poll_cluster#90.ang_range	1.395752***
	(0.184076)
40.poll_cluster#180.ang_range	0.850242***
	(0.114856)
40o.poll_cluster#270o.ang_range	0.000000
	(0.000000)

41.poll_cluster#0b.ang_range	0.666534***
	(0.107945)
41.poll_cluster#90.ang_range	1.153586***
	(0.028529)
41.poll_cluster#180.ang_range	1.157979***
	(0.071180)
41o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
42.poll_cluster#0b.ang_range	-0.514872***
	(0.076655)
42.poll_cluster#90.ang_range	-2.119304***
	(0.088464)
42.poll_cluster#180.ang_range	-1.638343***
	(0.086367)
42o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
43.poll_cluster#0b.ang_range	4.679211***
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43.poll_cluster#90.ang_range	4.261648***
	(0.191975)
43.poll_cluster#180.ang_range	0.168188
	(0.122952)
43o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
46.poll_cluster#0b.ang_range	4.123916***
	(0.149000)
46.poll_cluster#90.ang_range	2.799957***
	(0.288256)
46.poll_cluster#180.ang_range	-0.444641
	(0.297976)
46o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
47.poll_cluster#0b.ang_range	-1.073480
	(1.410970)
47.poll_cluster#90.ang_range	1.212940
	(1.137833)
47.poll_cluster#180.ang_range	0.100749
	(0.401057)
47o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
48.poll_cluster#0b.ang_range	2.170262***
	(0.126139)
48.poll_cluster#90.ang_range	0.071388
	(0.201102)
48.poll_cluster#180.ang_range	-0.292930***
	(0.105988)

48o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
49.poll_cluster#0b.ang_range	-0.438157***
	(0.152272)
49.poll_cluster#90.ang_range	-0.072123
	(0.216422)
49.poll_cluster#180.ang_range	0.617190***
	(0.201929)
49o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
50.poll_cluster#0b.ang_range	1.787376***
	(0.133246)
50.poll_cluster#90.ang_range	2.761226***
	(0.128676)
50.poll_cluster#180.ang_range	2.210137***
	(0.077735)
50o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
51.poll_cluster#0b.ang_range	1.091888***
	(0.148268)
51.poll_cluster#90.ang_range	1.113780***
	(0.107507)
51.poll_cluster#180.ang_range	0.489781***
	(0.111101)
51o.poll_cluster#270o.ang_range	0.000000
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52.poll_cluster#0b.ang_range	2.224656***
	(0.080003)
52.poll_cluster#90.ang_range	2.093280***
	(0.109649)
52.poll_cluster#180.ang_range	1.590405***
	(0.103631)
52o.poll_cluster#270o.ang_range	0.000000
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53.poll_cluster#0b.ang_range	1.812176***
	(0.085556)
53.poll_cluster#90.ang_range	3.330273***
	(0.106628)
53.poll_cluster#180.ang_range	1.409536***
	(0.077403)
53o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
54.poll_cluster#0b.ang_range	2.099165***
	(0.138157)
54.poll_cluster#90.ang_range	3.177539***
	(0.091200)

54.poll_cluster#180.ang_range	2.190554***
	(0.102587)
54o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
55.poll_cluster#0b.ang_range	0.444800***
	(0.142952)
55.poll_cluster#90.ang_range	1.742929***
	(0.439607)
55.poll_cluster#180.ang_range	2.232807***
	(0.490722)
55o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
58.poll_cluster#0b.ang_range	-0.584134**
	(0.256237)
58.poll_cluster#90.ang_range	0.522590
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58.poll_cluster#180.ang_range	2.041855***
	(0.761479)
58o.poll_cluster#270o.ang_range	0.000000
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59.poll_cluster#0b.ang_range	-2.046191***
	(0.105400)
59.poll_cluster#90.ang_range	-3.125409***
	(0.087334)
59.poll_cluster#180.ang_range	-2.038825***
	(0.158153)
59o.poll_cluster#270o.ang_range	0.000000
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60.poll_cluster#0b.ang_range	1.664617***
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60.poll_cluster#90.ang_range	3.181001***
	(0.173031)
60.poll_cluster#180.ang_range	2.027288***
	(0.088845)
60o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
61.poll_cluster#0b.ang_range	3.479542***
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61.poll_cluster#90.ang_range	3.845574***
	(0.133849)
61.poll_cluster#180.ang_range	1.966573***
	(0.076830)
61o.poll_cluster#270o.ang_range	0.000000
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62.poll_cluster#0b.ang_range	1.240450***
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62.poll_cluster#90.ang_range	2.951830***
	(0.094045)
62.poll_cluster#180.ang_range	1.354202***
	(0.084515)
62o.poll_cluster#270o.ang_range	0.000000
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64.poll_cluster#0b.ang_range	-0.529978***
	(0.195955)
64.poll_cluster#90.ang_range	1.721958***
	(0.369432)
64.poll_cluster#180.ang_range	1.562525***
	(0.329634)
64o.poll_cluster#270o.ang_range	0.000000
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65.poll_cluster#0b.ang_range	2.312312***
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65.poll_cluster#90.ang_range	3.607714***
	(0.152913)
65.poll_cluster#180.ang_range	1.274112***
	(0.168829)
65o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
66.poll_cluster#0b.ang_range	5.379033***
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66.poll_cluster#90.ang_range	2.623531***
	(0.323012)
66.poll_cluster#180.ang_range	-0.090753
	(0.217790)
66o.poll_cluster#270o.ang_range	0.000000
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67.poll_cluster#0b.ang_range	5.943604***
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67.poll_cluster#90.ang_range	6.437646***
	(0.202632)
67.poll_cluster#180.ang_range	0.841732***
	(0.088971)
67o.poll_cluster#270o.ang_range	0.000000
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70.poll_cluster#0b.ang_range	-0.077965
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70.poll_cluster#90.ang_range	0.299884
	(0.241782)
70.poll_cluster#180.ang_range	1.126774***
	(0.163560)
70o.poll_cluster#270o.ang_range	0.000000
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71.poll_cluster#0b.ang_range	3.537330***
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71.poll_cluster#90.ang_range	3.508613***
	(0.328092)
71.poll_cluster#180.ang_range	0.358017**
	(0.163549)
71o.poll_cluster#270o.ang_range	0.000000
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72.poll_cluster#0b.ang_range	3.100285***
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72.poll_cluster#90.ang_range	1.564728***
	(0.157913)
72.poll_cluster#180.ang_range	-0.098885
	(0.241870)
72o.poll_cluster#270o.ang_range	0.000000
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73.poll_cluster#0b.ang_range	1.222237***
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73.poll_cluster#90.ang_range	3.803236***
	(0.141715)
73.poll_cluster#180.ang_range	1.466282***
	(0.140764)
73o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
74.poll_cluster#0b.ang_range	2.435419***
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74.poll_cluster#90.ang_range	1.574590***
	(0.104957)
74.poll_cluster#180.ang_range	0.421916***
	(0.147743)
74o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
76.poll_cluster#0b.ang_range	1.826103***
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76.poll_cluster#90.ang_range	3.463895***
	(0.149195)
76.poll_cluster#180.ang_range	1.686707***
	(0.074675)
76o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
77.poll_cluster#0b.ang_range	0.544934***
	(0.141831)
77.poll_cluster#90.ang_range	1.546497***
	(0.229177)
77.poll_cluster#180.ang_range	0.755923***
	(0.200792)

77o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
78.poll_cluster#0b.ang_range	1.595192***
	(0.063375)
78.poll_cluster#90.ang_range	3.697810***
	(0.097097)
78.poll_cluster#180.ang_range	1.528540***
	(0.059593)
78o.poll_cluster#270o.ang_range	0.000000
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79.poll_cluster#0b.ang_range	1.003463***
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79.poll_cluster#90.ang_range	0.699692
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79.poll_cluster#180.ang_range	0.400529
	(0.391032)
79o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
81.poll_cluster#0b.ang_range	0.533267**
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81.poll_cluster#90.ang_range	0.299057
	(0.336135)
81.poll_cluster#180.ang_range	0.334238
	(0.205279)
81o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
82.poll_cluster#0b.ang_range	4.032507***
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82.poll_cluster#90.ang_range	3.787875***
	(0.342659)
82.poll_cluster#180.ang_range	0.093356
	(0.109890)
82o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
83.poll_cluster#0b.ang_range	1.239001***
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83.poll_cluster#90.ang_range	-1.063524***
	(0.194055)
83.poll_cluster#180.ang_range	-0.197006*
	(0.103482)
83o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
84.poll_cluster#0b.ang_range	0.484809
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84.poll_cluster#90.ang_range	0.228728
	(0.265732)

84.poll_cluster#180.ang_range	0.309210
	(0.277485)
84o.poll_cluster#270o.ang_range	0.000000
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85.poll_cluster#0b.ang_range	4.774645***
	(0.182782)
85.poll_cluster#90.ang_range	5.788659***
	(0.225577)
85.poll_cluster#180.ang_range	0.649450***
	(0.123128)
85o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
86.poll_cluster#0b.ang_range	-0.306621***
	(0.082773)
86.poll_cluster#90.ang_range	1.321408***
	(0.098699)
86.poll_cluster#180.ang_range	2.450896***
	(0.052875)
86o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
87.poll_cluster#0b.ang_range	2.349927***
	(0.063166)
87.poll_cluster#90.ang_range	2.378455***
	(0.092558)
87.poll_cluster#180.ang_range	1.288433***
	(0.060469)
87o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
88.poll_cluster#0b.ang_range	3.402868***
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88.poll_cluster#90.ang_range	1.928112***
	(0.184438)
88.poll_cluster#180.ang_range	-0.403807***
	(0.083048)
88o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
89.poll_cluster#0b.ang_range	-1.382257***
	(0.162155)
89.poll_cluster#90.ang_range	1.423189***
	(0.089005)
89.poll_cluster#180.ang_range	1.318561***
	(0.185310)
89o.poll_cluster#270o.ang_range	0.000000
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90.poll_cluster#0b.ang_range	-0.407911
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90.poll_cluster#90.ang_range	0.141854
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90.poll_cluster#180.ang_range	0.536553*
	(0.319704)
90o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
91.poll_cluster#0b.ang_range	0.915822***
	(0.092409)
91.poll_cluster#90.ang_range	1.775904***
	(0.183934)
91.poll_cluster#180.ang_range	1.682987***
	(0.086152)
91o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
92.poll_cluster#0b.ang_range	1.129919***
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92.poll_cluster#90.ang_range	2.734865***
	(0.136978)
92.poll_cluster#180.ang_range	2.197567***
	(0.063259)
92o.poll_cluster#270o.ang_range	0.000000
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94.poll_cluster#0b.ang_range	2.473007***
	(0.076610)
94.poll_cluster#90.ang_range	4.861084***
	(0.091280)
94.poll_cluster#180.ang_range	2.360137***
	(0.058945)
94o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
95.poll_cluster#0b.ang_range	2.938626***
	(0.096760)
95.poll_cluster#90.ang_range	4.710121***
	(0.093226)
95.poll_cluster#180.ang_range	2.042382***
	(0.084853)
95o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
96.poll_cluster#0b.ang_range	-0.768602
	(0.489317)
96.poll_cluster#90.ang_range	1.601669***
	(0.567302)
96.poll_cluster#180.ang_range	1.506609***
	(0.258459)
96o.poll_cluster#270o.ang_range	0.000000
	(0.000000)

97.poll_cluster#0b.ang_range	1.989814***
	(0.124956)
97.poll_cluster#90.ang_range	3.060489***
	(0.113097)
97.poll_cluster#180.ang_range	1.577659***
	(0.121320)
97o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
98.poll_cluster#0b.ang_range	0.087820
	(0.226270)
98.poll_cluster#90.ang_range	1.229115
	(0.943305)
98.poll_cluster#180.ang_range	1.766526***
	(0.630672)
98o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
99.poll_cluster#0b.ang_range	3.991946***
	(0.191849)
99.poll_cluster#90.ang_range	1.777721***
	(0.078841)
99.poll_cluster#180.ang_range	-0.209905
	(0.158230)
99o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
100.poll_cluster#0b.ang_range	4.642196***
	(0.122501)
100.poll_cluster#90.ang_range	3.463166***
	(0.159197)
100.poll_cluster#180.ang_range	-0.415264***
	(0.112539)
100o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
103.poll_cluster#0b.ang_range	1.479391***
	(0.294192)
103.poll_cluster#90.ang_range	0.672226
	(0.701548)
103.poll_cluster#180.ang_range	0.136409
	(0.268788)
103o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
104.poll_cluster#0b.ang_range	2.025529***
	(0.152859)
104.poll_cluster#90.ang_range	3.091357***
	(0.091056)
104.poll_cluster#180.ang_range	1.246586***
	(0.146518)

104o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
105.poll_cluster#0b.ang_range	1.519938***
	(0.118978)
105.poll_cluster#90.ang_range	3.577570***
	(0.076458)
105.poll_cluster#180.ang_range	2.400977***
	(0.072584)
105o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
106.poll_cluster#0b.ang_range	0.009745
	(0.260471)
106.poll_cluster#90.ang_range	0.712273
	(0.487918)
106.poll_cluster#180.ang_range	0.846522***
	(0.226045)
106o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
107.poll_cluster#0b.ang_range	1.495379***
	(0.129463)
107.poll_cluster#90.ang_range	2.249680***
	(0.164542)
107.poll_cluster#180.ang_range	2.003661***
	(0.076431)
107o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
109.poll_cluster#0b.ang_range	-0.470018
	(0.300372)
109.poll_cluster#90.ang_range	0.017754
	(0.348613)
109.poll_cluster#180.ang_range	0.498221*
	(0.302475)
109o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
110.poll_cluster#0b.ang_range	3.131638***
	(0.138795)
110.poll_cluster#90.ang_range	5.521875***
	(0.162977)
110.poll_cluster#180.ang_range	1.930624***
	(0.106886)
110o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
112.poll_cluster#0b.ang_range	5.278345***
	(0.187044)
112.poll_cluster#90.ang_range	2.070669***
	(0.200980)

112.poll_cluster#180.ang_range	0.202388*
	(0.105630)
112o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
115.poll_cluster#0b.ang_range	0.533713***
	(0.108098)
115.poll_cluster#90.ang_range	0.952290***
	(0.152207)
115.poll_cluster#180.ang_range	1.260022***
	(0.080462)
115o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
117.poll_cluster#0b.ang_range	1.754653***
	(0.144914)
117.poll_cluster#90.ang_range	3.529662***
	(0.156888)
117.poll_cluster#180.ang_range	2.498544***
	(0.103767)
117o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
118.poll_cluster#0b.ang_range	1.990507***
	(0.083857)
118.poll_cluster#90.ang_range	3.344773***
	(0.084817)
118.poll_cluster#180.ang_range	1.511566***
	(0.049072)
118o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
119.poll_cluster#0b.ang_range	-0.605435*
	(0.331944)
119.poll_cluster#90.ang_range	0.427004
	(0.511761)
119.poll_cluster#180.ang_range	0.823789**
	(0.366275)
119o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
120.poll_cluster#0b.ang_range	1.820096***
	(0.078763)
120.poll_cluster#90.ang_range	3.534257***
	(0.078469)
120.poll_cluster#180.ang_range	1.399368***
	(0.091815)
120o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
122.poll_cluster#0b.ang_range	4.145147***
	(0.105509)

122.poll_cluster#90.ang_range	5.753827***
	(0.158518)
122.poll_cluster#180.ang_range	1.391262***
	(0.114392)
122o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
123.poll_cluster#0b.ang_range	0.227820*
	(0.130778)
123.poll_cluster#90.ang_range	0.774530***
	(0.170063)
123.poll_cluster#180.ang_range	0.999130***
	(0.084742)
123o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
124.poll_cluster#0b.ang_range	1.313923***
	(0.127506)
124.poll_cluster#90.ang_range	0.931678***
	(0.098745)
124.poll_cluster#180.ang_range	0.599968***
	(0.097737)
124o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
125.poll_cluster#0b.ang_range	3.677131***
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125.poll_cluster#90.ang_range	2.461350***
	(0.233017)
125.poll_cluster#180.ang_range	-0.227303
	(0.158135)
125o.poll_cluster#270o.ang_range	0.000000
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127.poll_cluster#0b.ang_range	5.006985***
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127.poll_cluster#90.ang_range	6.354382***
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127.poll_cluster#180.ang_range	1.931227***
	(0.095378)
127o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
128.poll_cluster#0b.ang_range	2.302765***
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128.poll_cluster#90.ang_range	4.276665***
	(0.101957)
128.poll_cluster#180.ang_range	3.006704***
	(0.068915)
128o.poll_cluster#270o.ang_range	0.000000
	(0.000000)

129.poll_cluster#0b.ang_range	1.451518***
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129.poll_cluster#90.ang_range	2.497599***
	(0.323342)
129.poll_cluster#180.ang_range	1.643165***
	(0.465142)
129o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
130.poll_cluster#0b.ang_range	0.888868***
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130.poll_cluster#90.ang_range	0.850984***
	(0.202659)
130.poll_cluster#180.ang_range	0.548061***
	(0.147528)
130o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
131.poll_cluster#0b.ang_range	-0.275537
	(0.219585)
131.poll_cluster#90.ang_range	-0.122585
	(0.168154)
131.poll_cluster#180.ang_range	0.559008***
	(0.201139)
131o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
133.poll_cluster#0b.ang_range	6.341920***
	(0.163961)
133.poll_cluster#90.ang_range	7.722789***
	(0.315888)
133.poll_cluster#180.ang_range	1.733008***
	(0.106852)
133o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
134.poll_cluster#0b.ang_range	3.776768***
	(0.179886)
134.poll_cluster#90.ang_range	2.911384***
	(0.230254)
134.poll_cluster#180.ang_range	0.093669
	(0.102145)
134o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
135.poll_cluster#0b.ang_range	-4.591385***
	(0.408428)
135.poll_cluster#90.ang_range	-3.208094***
	(0.302801)
135.poll_cluster#180.ang_range	0.964074*
	(0.563164)

135o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
136.poll_cluster#0b.ang_range	2.844620***
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136.poll_cluster#90.ang_range	4.327178***
	(0.221003)
136.poll_cluster#180.ang_range	1.138129***
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136o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
137.poll_cluster#0b.ang_range	0.837019***
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137.poll_cluster#90.ang_range	2.798002***
	(0.105812)
137.poll_cluster#180.ang_range	1.037849***
	(0.072089)
137o.poll_cluster#270o.ang_range	0.000000
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138.poll_cluster#0b.ang_range	0.066326
	(0.114395)
138.poll_cluster#90.ang_range	-1.031696***
	(0.148307)
138.poll_cluster#180.ang_range	0.166859*
	(0.085294)
138o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
139.poll_cluster#0b.ang_range	2.502838***
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139.poll_cluster#90.ang_range	1.221601***
	(0.116202)
139.poll_cluster#180.ang_range	0.309008***
	(0.077914)
139o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
140.poll_cluster#0b.ang_range	4.968246***
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140.poll_cluster#90.ang_range	5.981953***
	(0.205503)
140.poll_cluster#180.ang_range	1.843864***
	(0.121001)
140o.poll_cluster#270o.ang_range	0.000000
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141.poll_cluster#0b.ang_range	2.698651***
	(0.266333)
141.poll_cluster#90.ang_range	2.634367***
	(0.206808)

141.poll_cluster#180.ang_range	0.557174***
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141o.poll_cluster#270o.ang_range	0.000000
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142.poll_cluster#0b.ang_range	-0.094960
	(0.392779)
142.poll_cluster#90.ang_range	0.056107
	(0.414479)
142.poll_cluster#180.ang_range	1.677557***
	(0.567643)
142o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
143.poll_cluster#0b.ang_range	1.744299***
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143.poll_cluster#90.ang_range	3.467672***
	(0.125099)
143.poll_cluster#180.ang_range	2.047649***
	(0.083541)
143o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
144.poll_cluster#0b.ang_range	1.704313***
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144.poll_cluster#90.ang_range	3.344019***
	(0.100567)
144.poll_cluster#180.ang_range	2.132869***
	(0.078267)
144o.poll_cluster#270o.ang_range	0.000000
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145.poll_cluster#0b.ang_range	0.304116
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145.poll_cluster#90.ang_range	1.452138
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145.poll_cluster#180.ang_range	1.625433*
	(0.887678)
145o.poll_cluster#270o.ang_range	0.000000
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148.poll_cluster#0b.ang_range	1.003240***
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148.poll_cluster#90.ang_range	2.767941***
	(0.038700)
148.poll_cluster#180.ang_range	1.399731***
	(0.046783)
148o.poll_cluster#270o.ang_range	0.000000
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149.poll_cluster#0b.ang_range	2.369887***
	(0.095061)

149.poll_cluster#90.ang_range	1.796273***
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149.poll_cluster#180.ang_range	0.871462***
	(0.109607)
149o.poll_cluster#270o.ang_range	0.000000
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150.poll_cluster#0b.ang_range	2.196984
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150.poll_cluster#90.ang_range	2.062069
	(1.827293)
150.poll_cluster#180.ang_range	-1.301490
	(0.815912)
150o.poll_cluster#270o.ang_range	0.000000
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151.poll_cluster#0b.ang_range	0.659729***
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151.poll_cluster#90.ang_range	1.274982***
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151.poll_cluster#180.ang_range	1.353439***
	(0.067696)
151o.poll_cluster#270o.ang_range	0.000000
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152.poll_cluster#0b.ang_range	-0.683034***
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152.poll_cluster#90.ang_range	0.135930
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152.poll_cluster#180.ang_range	0.477758***
	(0.073861)
152o.poll_cluster#270o.ang_range	0.000000
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154.poll_cluster#0b.ang_range	-0.635512***
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154.poll_cluster#90.ang_range	-0.286976
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154.poll_cluster#180.ang_range	0.061309
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154o.poll_cluster#270o.ang_range	0.000000
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156.poll_cluster#0b.ang_range	4.259030***
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156.poll_cluster#90.ang_range	5.900223***
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156.poll_cluster#180.ang_range	1.590715***
	(0.129108)
156o.poll_cluster#270o.ang_range	0.000000
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157.poll_cluster#0b.ang_range	2.469101***
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157.poll_cluster#90.ang_range	2.180887***
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157.poll_cluster#180.ang_range	1.296182***
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157o.poll_cluster#270o.ang_range	0.000000
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158.poll_cluster#0b.ang_range	0.946947***
	(0.366349)
158.poll_cluster#90.ang_range	0.716450**
	(0.300740)
158.poll_cluster#180.ang_range	1.058712***
	(0.200810)
158o.poll_cluster#270o.ang_range	0.000000
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160.poll_cluster#0b.ang_range	0.961810***
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160.poll_cluster#90.ang_range	2.749685***
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160.poll_cluster#180.ang_range	1.485634***
	(0.050614)
160o.poll_cluster#270o.ang_range	0.000000
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161.poll_cluster#0b.ang_range	0.748096***
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161.poll_cluster#90.ang_range	2.302867***
	(0.102519)
161.poll_cluster#180.ang_range	1.029191***
	(0.107635)
161o.poll_cluster#270o.ang_range	0.000000
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162.poll_cluster#0b.ang_range	-0.371181
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162.poll_cluster#90.ang_range	0.862109**
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162.poll_cluster#180.ang_range	1.831291***
	(0.640958)
162o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
163.poll_cluster#0b.ang_range	2.682191***
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163.poll_cluster#90.ang_range	0.925884***
	(0.176314)
163.poll_cluster#180.ang_range	-0.657941***
	(0.153033)

163o.poll_cluster#270o.ang_range	0.000000
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164.poll_cluster#0b.ang_range	-0.859730***
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164.poll_cluster#90.ang_range	-0.212231
	(0.306999)
164.poll_cluster#180.ang_range	-0.060566
	(0.211230)
164o.poll_cluster#270o.ang_range	0.000000
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165.poll_cluster#0b.ang_range	-0.989570***
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165.poll_cluster#90.ang_range	-2.167839***
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165.poll_cluster#180.ang_range	-1.738329***
	(0.408502)
165o.poll_cluster#270o.ang_range	0.000000
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167.poll_cluster#0b.ang_range	-0.948229***
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167.poll_cluster#90.ang_range	0.678972*
	(0.376550)
167.poll_cluster#180.ang_range	1.602315***
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167o.poll_cluster#270o.ang_range	0.000000
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168.poll_cluster#0b.ang_range	1.251942***
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168.poll_cluster#90.ang_range	2.546530***
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168.poll_cluster#180.ang_range	1.369905***
	(0.129989)
168o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
169.poll_cluster#0b.ang_range	-0.157463
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169.poll_cluster#90.ang_range	0.083926
	(0.104353)
169.poll_cluster#180.ang_range	0.910831***
	(0.088955)
169o.poll_cluster#270o.ang_range	0.000000
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170.poll_cluster#0b.ang_range	-0.802594*
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170.poll_cluster#90.ang_range	-1.068181**
	(0.474840)

170.poll_cluster#180.ang_range	-0.278853
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170o.poll_cluster#270o.ang_range	0.000000
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171.poll_cluster#0b.ang_range	0.891880***
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171.poll_cluster#90.ang_range	-0.164091
	(0.242575)
171.poll_cluster#180.ang_range	0.693168***
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171o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
172.poll_cluster#0b.ang_range	5.158632***
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172.poll_cluster#90.ang_range	5.303547***
	(0.206210)
172.poll_cluster#180.ang_range	0.952832***
	(0.119396)
172o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
173.poll_cluster#0b.ang_range	-0.169509
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173.poll_cluster#90.ang_range	1.235310***
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173.poll_cluster#180.ang_range	-0.054023
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173o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
174.poll_cluster#0b.ang_range	0.298099
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174.poll_cluster#90.ang_range	2.031254***
	(0.243236)
174.poll_cluster#180.ang_range	1.686156***
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174o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
175.poll_cluster#0b.ang_range	0.162523
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175.poll_cluster#90.ang_range	-0.348634
	(0.230017)
175.poll_cluster#180.ang_range	-0.619542***
	(0.183800)
175o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
176.poll_cluster#0b.ang_range	2.131629***
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176.poll_cluster#90.ang_range	3.667721***
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176.poll_cluster#180.ang_range	2.646855***
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176o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
177.poll_cluster#0b.ang_range	-0.359044**
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177.poll_cluster#90.ang_range	0.088319
	(0.196471)
177.poll_cluster#180.ang_range	0.819916***
	(0.062208)
177o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
178.poll_cluster#0b.ang_range	1.829982***
	(0.120018)
178.poll_cluster#90.ang_range	2.208291***
	(0.120154)
178.poll_cluster#180.ang_range	0.777756***
	(0.073721)
178o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
179.poll_cluster#0b.ang_range	-1.093473
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179.poll_cluster#90.ang_range	-0.234509
	(0.407007)
179.poll_cluster#180.ang_range	-0.640913***
	(0.228960)
179o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
180.poll_cluster#0b.ang_range	-0.078483
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180.poll_cluster#90.ang_range	0.382905
	(0.238734)
180.poll_cluster#180.ang_range	-0.304803
	(0.282300)
180o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
181.poll_cluster#0b.ang_range	-1.185844
	(1.409439)
181.poll_cluster#90.ang_range	-1.064855
	(1.208516)
181.poll_cluster#180.ang_range	-2.553860***
	(0.461464)
181o.poll_cluster#270o.ang_range	0.000000
	(0.000000)

182.poll_cluster#0b.ang_range	-0.947691***
	(0.280257)
182.poll_cluster#90.ang_range	0.197641
	(0.468842)
182.poll_cluster#180.ang_range	0.924393
	(0.597968)
182o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
183.poll_cluster#0b.ang_range	1.453636***
	(0.110257)
183.poll_cluster#90.ang_range	3.854372***
	(0.114798)
183.poll_cluster#180.ang_range	1.719645***
	(0.084170)
183o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
184.poll_cluster#0b.ang_range	2.533359***
	(0.106151)
184.poll_cluster#90.ang_range	3.085518***
	(0.148593)
184.poll_cluster#180.ang_range	1.212567***
	(0.135626)
184o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
186.poll_cluster#0b.ang_range	-1.160408***
	(0.329584)
186.poll_cluster#90.ang_range	0.653763**
	(0.290812)
186.poll_cluster#180.ang_range	1.188235***
	(0.427988)
186o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
187.poll_cluster#0b.ang_range	0.116318
	(0.407580)
187.poll_cluster#90.ang_range	0.172235
	(0.613612)
187.poll_cluster#180.ang_range	-0.259806
	(0.239720)
187o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
188.poll_cluster#0b.ang_range	5.613249***
	(0.217449)
188.poll_cluster#90.ang_range	2.001138***
	(0.179020)
188.poll_cluster#180.ang_range	0.463536***
	(0.139739)

188o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
189.poll_cluster#0b.ang_range	-0.812685*
	(0.446854)
189.poll_cluster#90.ang_range	2.198955***
	(0.828166)
189.poll_cluster#180.ang_range	1.262276***
	(0.451696)
189o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
190.poll_cluster#0b.ang_range	0.094324
	(0.138257)
190.poll_cluster#90.ang_range	-0.222745*
	(0.119170)
190.poll_cluster#180.ang_range	0.242428*
	(0.136167)
190o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
191.poll_cluster#0b.ang_range	1.653324***
	(0.112230)
191.poll_cluster#90.ang_range	3.868206***
	(0.111128)
191.poll_cluster#180.ang_range	1.782372***
	(0.069278)
191o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
192.poll_cluster#0b.ang_range	1.940781***
	(0.176037)
192.poll_cluster#90.ang_range	3.772523***
	(0.130452)
192.poll_cluster#180.ang_range	1.789697***
	(0.076642)
192o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
193.poll_cluster#0b.ang_range	1.770616
	(1.277970)
193.poll_cluster#90.ang_range	1.387669
	(0.996782)
193.poll_cluster#180.ang_range	-0.650433
	(0.740139)
193o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
194.poll_cluster#0b.ang_range	0.151399
	(0.271773)
194.poll_cluster#90.ang_range	0.156003
	(0.231919)

194.poll_cluster#180.ang_range	0.061704
	(0.161361)
194o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
195.poll_cluster#0b.ang_range	0.708519***
	(0.141139)
195.poll_cluster#90.ang_range	0.973760***
	(0.240009)
195.poll_cluster#180.ang_range	0.481221
	(0.295006)
195o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
196.poll_cluster#0b.ang_range	-0.913288
	(1.307208)
196.poll_cluster#90.ang_range	1.646746
	(1.367180)
196.poll_cluster#180.ang_range	0.034782
	(0.907179)
196o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
197.poll_cluster#0b.ang_range	3.226251***
	(0.099918)
197.poll_cluster#90.ang_range	4.710354***
	(0.114311)
197.poll_cluster#180.ang_range	1.259862***
	(0.100766)
197o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
198.poll_cluster#0b.ang_range	-0.340742
	(0.241652)
198.poll_cluster#90.ang_range	0.879695**
	(0.377379)
198.poll_cluster#180.ang_range	0.834227***
	(0.225952)
198o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
199.poll_cluster#0b.ang_range	-0.745451
	(1.109478)
199.poll_cluster#90.ang_range	4.317208***
	(0.618195)
199.poll_cluster#180.ang_range	6.119289***
	(0.527549)
199o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
200.poll_cluster#0b.ang_range	-1.107133***
	(0.418563)

200.poll_cluster#90.ang_range	1.110151**
	(0.474065)
200.poll_cluster#180.ang_range	1.762158***
	(0.346800)
200o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
Observations	8,262,768

Notes: This table depicts our first stage, which is the association of daily wind direction and daily PM2.5 concentrations. "ang_range" are a set of binary variables equal to one if the daily average wind direction in county i falls within the relevant 90 degree interval [90b, 90b + 90) (and zero otherwise). The omitted category is the interval [270,360). We interact these binary wind direction variables with our 200 pollution clusters (defined by the poll_cluster dummy variables). Therefore, our coefficient of interest is allowed to vary across geographic regions.

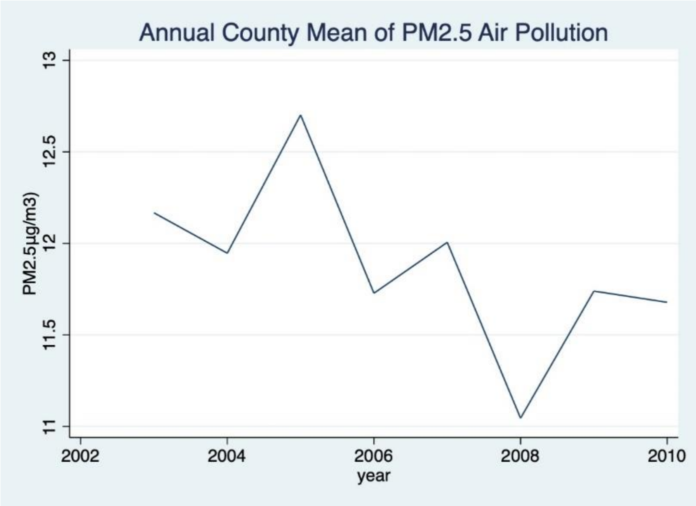
Table A2: Effects of PM2.5 Using Longer Time Windows and Only Pollution Monitor Data

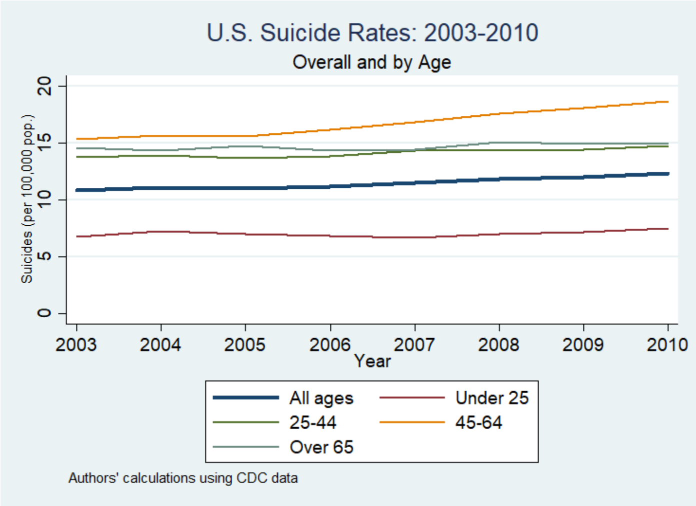
	(1) Log of 3-day Suicides	(2) Log of 7-Day Suicides
	Panel A: Effects of PM2.5 Using Longer Time Windows	
Daily PM2.5	0.002023*	0.001527**
	(0.001126)	(0.000625)
Mean of Outcome	0.071509	0.1309
F-Statistic	7685	9521
Observations	8243810	8231456
	Panel B: Effects of PM2.5 on Suicides Using Pollution Monitor Data Only	
	(3) Log Daily PM2.5 (IV)	(4) Log Daily PM2.5 (OLS)
Daily PM2.5	0.003225**	-0.000552
	(0.001581)	(0.000415)
Mean of Outcome	0.090066	0.090066
F-Statistic	69619	--
Observations	1447750	1447750

Notes: Panel A of this table reports the effect of PM2.5 on suicide deaths using a three day model in Column 1, and a seven day model in Column 2. Panel B reports the association between PM2.5 and daily deaths from suicide using only data from pollution monitors. Column 3 uses our preferred 2SLS specification and Column 4 uses OLS. All regressions control for county, state-month, month-year and day of week fixed effects, holidays, total population, deciles of average temperature, precipitation, and wind speed, and the unemployment rate. Standard errors are clustered at the county level and are in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

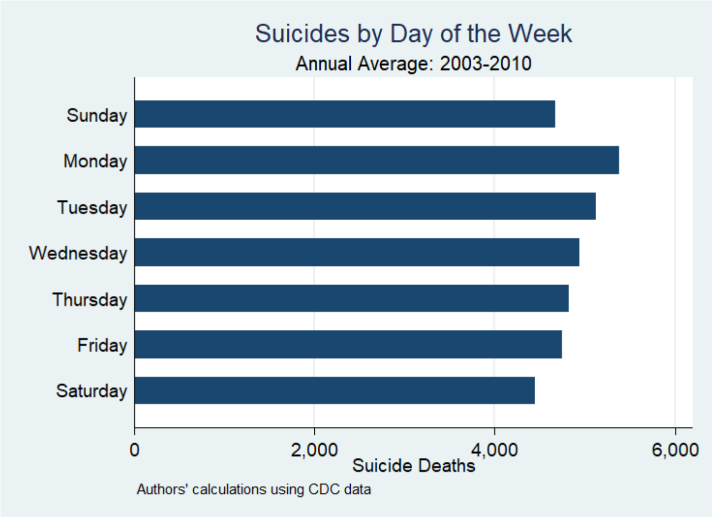
Figure A1: Trends in Suicides over Time and Day of the Week

Panel A Panel B





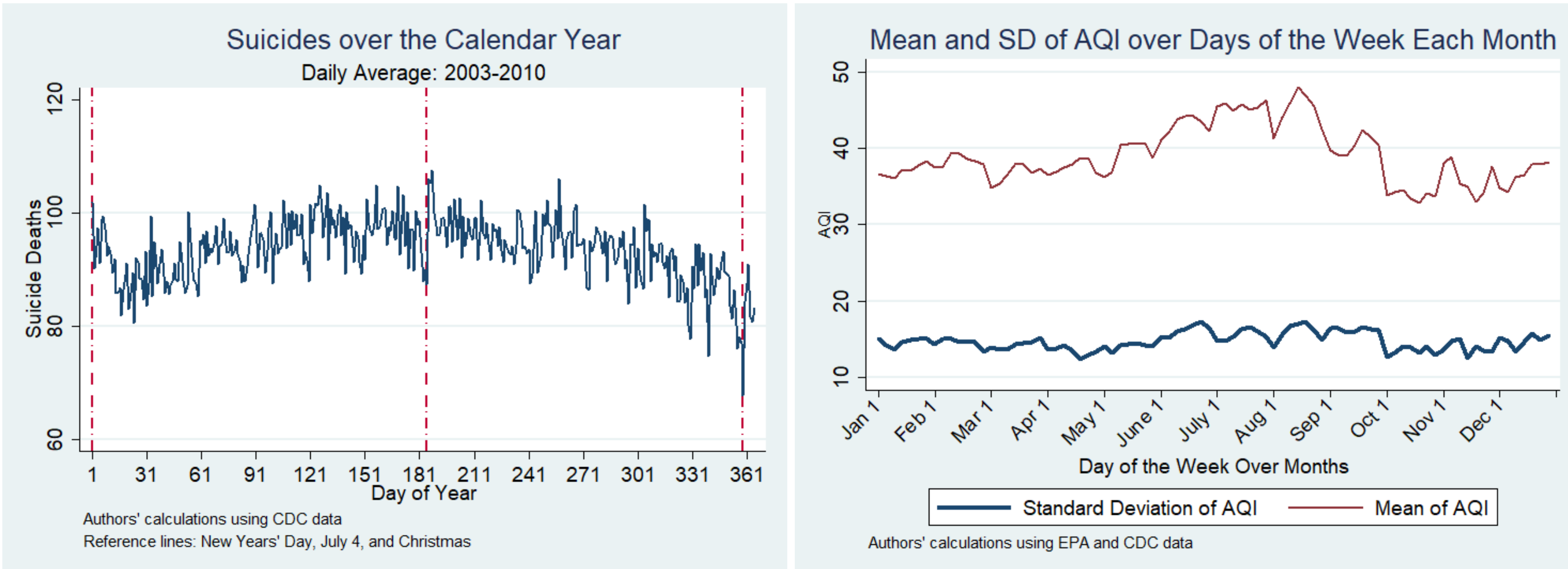
Panel C



Notes: Panel A of Figure A1 shows the annual county mean of PM2.5 pollution over time. PM2.5 concentrations show some variety over the sample period. Panel B depicts trends in suicides by age over our sample's time period. Panel C depicts how suicides vary over day of the week.

Figure A2: Variation over Time in Suicides and AQI

Panel A Panel B



Notes: Panel A of Figure A2 depicts the variation over time in suicides over the day of the year. Panel B shows the mean and standard deviation of the AQI over days of the week each month.