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DISCUSSION PAPER SERIES

IZA DP No. 15087

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ABSTRACT

Air Quality and Suicide*

Though there is clinical evidence linking pollution induced inflammatory factors and major depression and suicide, no definitive study of risk in the community exists. In this study, we provide the first population-based estimates of the relationship between air pollution and suicide in the United States. Using detailed cause of death data from all death certificates in the U.S. between 2003 and 2010, we estimate the relationship between daily variation in air quality measured using NASA satellite data, and suicide rates. Using wind direction as an instrument for reducing potentially endogeneity and measurement error in daily pollution exposure, we find that a 1 μg/m^3 increase in daily PM2.5 is associated with a 0.49 percent increase in daily suicides (a 19.3 percent increase). We also estimate the impact of days with high air pollution on contemporaneous suicide rates compared to other days in the same state-month, month-year, day of the week and county with lower air pollution, conditional on the same weather and total population. 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.

JEL Classification: I10, Q52, Q53

Keywords: air pollution, suicide, health

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I. Introduction

The evidence establishing air pollution as a health hazard impacting human capital is substantial and expanding. 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 shown to reduce performance on academic tests of many types (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 cognitive functioning, 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), 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 and is 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 are on the rise in the United States (U.S.), having increased by nearly 50% between 2000 and 2019.[1] Suicide is now the tenth leading cause of death, claiming the lives of 47,511 Americans in 2019. The study of suicide and how rates vary has been a topic of study 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 the population 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 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 clinical trials of neuropsychiatric medications (Gunnell et al., 2005) 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).

[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.

In this paper, we conduct the first-ever large-scale study of how pollution affects 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 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 state-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 PM2.5 is associated with a 0.49 percent increase in daily suicides (a 19.3 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.

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 daily data over many years for all counties in the U.S.

Second, our study includes a methodological innovation over the existing literature on the health effects of pollution by using an instrumental variables (IV) design and a daily county panel that allows us to include a large number of location and time fixed effects. We compare different days in the same month in the same state-county, year and day of the week that happen to randomly differ in the amount of ambient air pollution because of daily variations in wind direction to estimate whether days with higher pollution have higher rates of suicide, compared with other counties on the same days. Our IV model builds on a difference in difference specification where we compare daily variation in pollution in a county, compared to variation in other counties in the same state over the same time using month, year, state-county and day of the week fixed effects, as well as controls for weather, population and holidays. 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. However, our instrumental variables design better addresses measurement error in pollution by using daily pollution that affects an entire county at once because it is carried on the wind.

Third, we estimate the effects of contemporaneous versus chronic pollution exposure using an event study design in which we regress weekly pollution levels leading up to the event on suicides in those weeks. This sheds light on the temporal mechanisms through which air pollution could lead to suicide.

Because we have sufficient power, we also investigate what specific types of pollution, such as PM2.5, PM10, nitrous oxide, ozone, and sulfur dioxide are most likely to increase suicidality. We also investigate whether more population-dense, poor, 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. Finally, we also are the first to investigate how these effects might vary by age, gender and race.

II. 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. In clinical settings and research on survivors, this is referred to as a "cry for help" (Maple et al., 2020). Unfortunately, due to data limitations, we are unable to determine which of these factors contributes most to our results. However, we next review the evidence on these factors.

Airborne fine particulate matter and toxins 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 good amount of work 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, Kunn, Palacios and Pestel (2019) find that chess players are more likely to make mistakes in games on days with higher air pollution. 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).

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 et al (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.

III. Description of the Data

To advance our understanding of the impact of pollution on suicide in the U.S., we exploit daily data on deaths by type collected by the CDC from all state vital records offices, also matched to weather data from the CDC and the NOAA, data on daily Air Quality Index (AQI) data from the EPA and CDC, and additional county data from the Census and Bureau of Labor Statistics. We collected data on wind speed and wind direction data from the North American Regional Reanalysis (NARR) daily reanalysis 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 also obtain additional temperature and precipitation data from Deryugina et al (2019), who use data from PRISM and weather stations to obtain an average daily measure of temperature and precipitation in each county.

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] This is the most comprehensive panel of mortality data to date. One big advantage of such a large panel of data is that our data set does not suffer from selection bias since it includes all deaths in the United States over this period that were ruled suicides in all 3007 counties in the United States.

The EPA data include daily data on the Air Quality Index, which is a scale between 0 and 500 indicating the amount of pollution in the air. Higher scores indicate more air pollution. The AQI is predominantly determined by Particulate Matter 2.5 (PM2.5) and ozone. 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 and precipitation at the county level and data from NOAA on temperature, precipitation, wind speed, 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 Figure 1, PM2.5 decreases in the first part of the sample period and then increases overall.

We match these data to county-level data on demographics and unemployment from the Census and Bureau of Labor Statistics. Table 1 shows the average county characteristics,

[3] These detailed cause of death data are unavailable for more recent years.

pollution levels, and suicide rates between 2003-2010 for the counties in our sample, which includes nearly all counties in the United States.

IV. Identification Strategy

To estimate the effect of pollution on suicide, we first estimate the relation 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, 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 ultrafine particulate matter (PM2.5) in the county, measured in μg/m^3. W_{idmy} are daily weather controls for temperature and precipitation 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. 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.

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.

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 substantial distances 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.[4] 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, day, state-month, month-year and day of the week fixed effects, as well as temperature, precipitation and holidays.[5] 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 is:

[4] See, for example, https://www.nytimes.com/interactive/2021/07/21/climate/wildfire-smoke-map.html
[5] A similar identification strategy was used by Deryugina et al (2019) to estimate the effects of PM2.5 on all-cause mortality.

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

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 2 shows counties assigned to each monitor group. $1[G_c = g]$ is a set of binary 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 3 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 967.72.

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.

V. Results

A. Results on Suicides

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. 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 19.3 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. Compared to the OLS estimates, the IV estimates are larger, more positive and statistically significant. This is consistent with because measurement error creates attenuation bias in our estimates for the reasons we discussed above.

Because deaths from suicide might occur with some lag, we also estimate a three-day measure of suicides in Column 3 of Table 2, 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. 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.[6]

The relative importance of contemporaneous pollution is corroborated by our event study results, presented in Figure 4 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 4, 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.

B. 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 3, we present results in which

[6] The results are even smaller using a five-day model.

we include other pollutants in the same model, allowing wind to instrument for different types of pollution conditional on the other pollutants. 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.

Since residential segregation, economic and biological factors might increase risk for some groups, we next examine the results by race and gender in Table 4. 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. 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.

Because suicide risk and time spent outdoors varies by age, in Table 5 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. 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. This might be because younger people are more likely to be exposed to higher levels of pollution from commuting and being outdoors during rush hours. 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.

C. Additional Threats to Internal Validity and Other Outcomes

In any observational study where treatment cannot be randomized, threats to validity for interpreting outcome difference between treated and control subjects are possible. 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 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 5. 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.

To investigate the validity of the monotonicity assumption, in Table 6, 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. This suggests that the number of monitor groups (and any potential monotonicity violations) has little effect on our estimates. Thus, we can interpret our estimates 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 7 presents the results of this placebo analysis. Columns 1 through 5 show the results of our main specification on deaths from Lyme disease, congenital anomalies, hernias, metabolic disorders, and digestive diseases. None of the estimates are statistically significant at conventional levels, and all are near zero.

In columns 6-8 of Table 7 we show results from estimating our main specification on causes of death that are known to be affected by pollution: diabetes, 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 0.368 percent increase in daily diabetes deaths, a 0.331 percent increase in daily COPD deaths, and a 0.295 percent increase in daily heart attack deaths.

In Table 8, 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 were suicide is a rare event, in column 1 of Table 8, 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. 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 3 of Table 8, we add day fixed effects to our main instrumental variables specification and find very similar results. Finally, 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 4 of Table 8.

Reassuringly, the coefficient using PPML is very similar to that in our primary specification in Table 2.

VI. Conclusion

This is the first study showing that air pollution increases suicides. Using daily wind direction as an instrument for daily ultrafine particulate matter exposure, we find that a 1 $\mu g/m^3$ increase in PM2.5 leads to a 0.5 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, diabetes and ischemic heart attack.

In our preferred instrumental variables model, we find that a 1 $\mu g/m^3$ 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. These results imply that on a day with PM2.5 at the threshold of unhealthy levels (35 $\mu g/m^3$), 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 $\mu g/m^3$). [7] This is a small number, but it is a daily risk. So, in a county with a million resident, 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 $\mu g/m^3$ increase in PM2.5 over this time period on suicide deaths. We find that a 1 $\mu g/m^3$ increase in

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

PM2.5 on each day over a year would lead to 153.8 additional suicides in that year.[8] 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 increases and decreases over time in average annual amounts of PM2.5 during our study period (as shown in Figure 1).

Our work offers several important lessons for policy and treatment of depression. Understanding how air pollution impacts suicide risk will allow policymakers to target resources to places when there are likely to be greater risks. In addition, this research contributes to our understanding of the environmental processes that impact suicidality and the true costs of pollution. If certain types of pollution are most likely to increase suicide risks, we may be able to better regulate those types of pollutants. One last implication of this work is more direct for physicians and those who have persons at risk in their families. In the public health world, efforts to temporarily take guns from the suicidal appear to be protective (see the work of David Hemenway among others). If air pollution is a risk, then interventions to keep those at risk of suicide indoors or refrain from strenuous activity outdoors might make sense. For example, air purifiers could be employed in in-patient facilities that treat depressed patients on high air pollution days.

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[8] 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.

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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	88.3
	[242]
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 daily suicides (1 day model)	(2) Log daily suicide rate	(3) Log daily suicides (3 day model)	(3) Log All Deaths
	Panel A: OLS Estimates			
Average daily PM 2.5, micrograms per cubic meter	-0.000461	-0.000063	0.001480	0.000545***
	(0.000367)	(0.000078)	(0.001290)	(0.000059)
	Panel B: IV Estimates			
Average daily PM 2.5, micrograms per cubic meter	0.004914***	0.004038**	0.002023*	0.003577***
	(0.001675)	(0.001902)	(0.001126)	(0.000236)
Mean of Outcome	0.0255	0.0623	0.0715	0.7842
Observations	8262736	8262736	8243810	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, Column 2 shows estimates for the log of the daily suicide rate per million people, and Column 2 shows estimates for the log of all daily deaths. Panel A reports estimates using wind as an instrument for pollution. Our primary specification uses 200 monitor groups. Panel B reports estimates using OLS regression. All regressions control for county, state-month, month-year and day of week FEs, holidays, total population, deciles of average temperature, and precipitation, wind speed, and 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 Different Pollutants on log of suicide using state-month, month-year, county, and day of the week FEs

	Log Suicides				
	(1) Adjusted PM25	(2) Adjusted SO2	(3) Adjusted O3	(4) Adjusted CO	(5) Adjusted NO2
Different Pollutants	0.077578**	0.050681	-0.016548	-0.003576*	-0.041641
	(0.034646)	(0.077261)	(0.029018)	(0.001887)	(0.055045)
Mean of Outcome	0.2492	0.2492	0.2492	0.2492	0.2492
Observations	210426	210426	210426	210426	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. All regressions control for county, state-month, month-year and day of week FEs, holidays, total population, deciles of average temperature, and precipitation, wind speed, and unemployment rate. Standard errors are clustered at the county level and are in parentheses.

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

Table 4: Heterogeneity by Race, Gender and Education

	Log Suicides			
	(1)	(2)	(3)	(4)
	White	Black	Female	Male
Daily PM 2.5	0.003925**	0.006855	0.00487	0.00458**
	(0.001793)	(0.007107)	(0.00364)	(0.00190)
Mean of Outcome	0.02338	0.001445	0.00547	0.02041
Observations	8262736	8262736	8262736	8262736

Notes: This table reports the effect of daily PM2.5 on the log of daily suicide deaths for different groups. 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 5-8 show the results for people with different levels of education. Our primary specification uses 200 monitor groups. All regressions control for county, state-month, month-year and day of week FEs, holidays, total population, deciles of average temperature, and precipitation, wind speed, and unemployment rate. Standard errors are clustered at the county level and are in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 5: 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 PM 2.5	-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
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 FEs, holidays, total population, deciles of average temperature, and precipitation, wind speed, and unemployment rate. Standard errors are in parentheses.

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

Table 6: 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, micrograms per cubic meter	0.004080** (0.001641)
	Panel B: 300 Monitor Groups
Average daily PM 2.5, micrograms per cubic meter	0.004459*** (0.001658)
	Panel C: 400 Monitor Groups
Average daily PM 2.5, micrograms per cubic meter	0.004313** (0.001688)
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 FEs, holidays, total population, deciles of average temperature, and precipitation, wind speed, and unemployment rate. Standard errors are clustered at the county level and are in parentheses.

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

Table 7: Effect of PM2.5 on Placebo deaths and Air Pollution-related Deaths

	Placebo Causes of Death					*Deaths Related to Air Pollution*		
	(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 Diabetes	(7) Log Deaths from Chronic Obstructive Pulmonary Disease	(8) Log Deaths from Ischemic Heart Attack
Daily PM 2.5	-0.01492	0.00341	0.00198	0.00142	0.00256	0.00368***	0.00331***	0.00295***
	(0.13661)	(0.00384)	(0.00868)	(0.00291)	(0.00259)	(0.00123)	(0.00087)	(0.00048)
Mean of Outcome	0.00001	0.00654	0.00115	0.01154	0.01438	0.05063	0.08967	0.25277
Observations	8262736	8262736	8262736	8262736	8262736	8262736	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 FEs, holidays, total population, deciles of average temperature, and precipitation, wind speed, and unemployment rate. Standard errors are in parentheses.

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

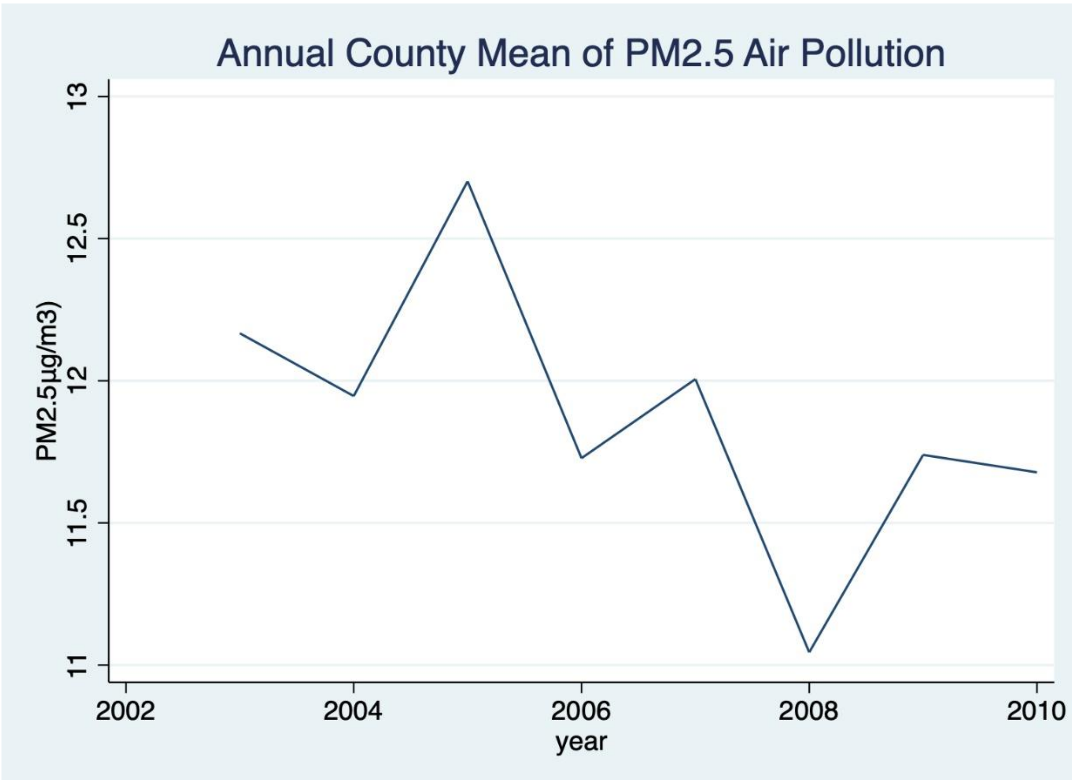
Table 8: Results for Alternative Samples and Alternative Specifications

	Log Suicides			
	(1) Limiting to Counties with >10,000 people	(2) Limiting to Counties that ever had 2 or more suicides/day	(3) Using Day Fixed Effects	(4) Using PPML with IV
Daily PM 2.5	0.005849***	0.008233**	0.004914***	0.003870***
	(0.001896)	(0.003630)	(0.001675)	(0.001262)
Mean of Outcome	0.031839	0.064045	0.025543	0.025543
Observations	6522413	2698046	8262736	8182898

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 presents the results of our primary specification when adding day of the month fixed effects. Column 4 presents the results when using PPML in the IV rather than OLS. All regressions control for county, state-month, month-year and day of week FEs, holidays, total population, deciles of average temperature, and precipitation, wind speed, and unemployment rate. Standard errors are clustered at the county level and are in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

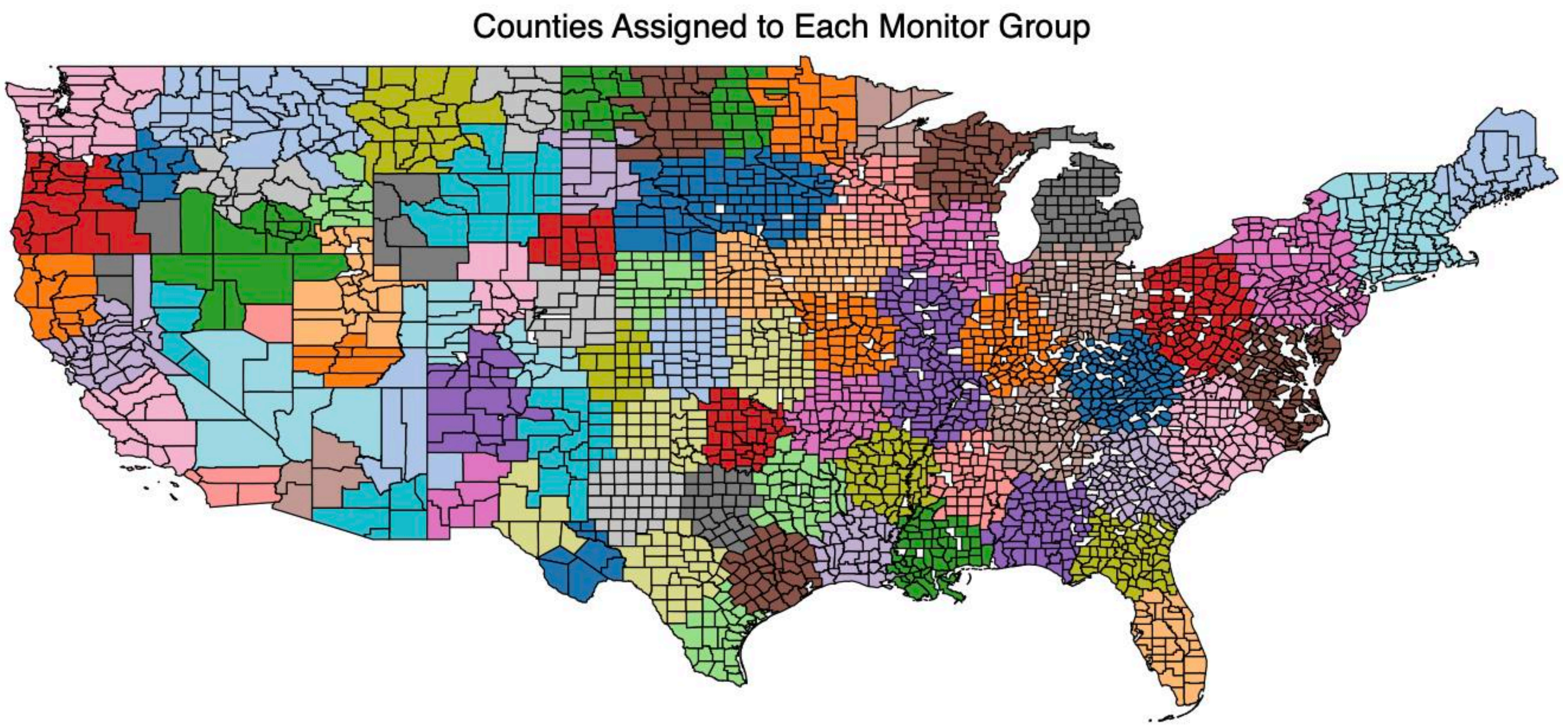
Figures

Figure 1: Annual County-level PM2.5 over Time



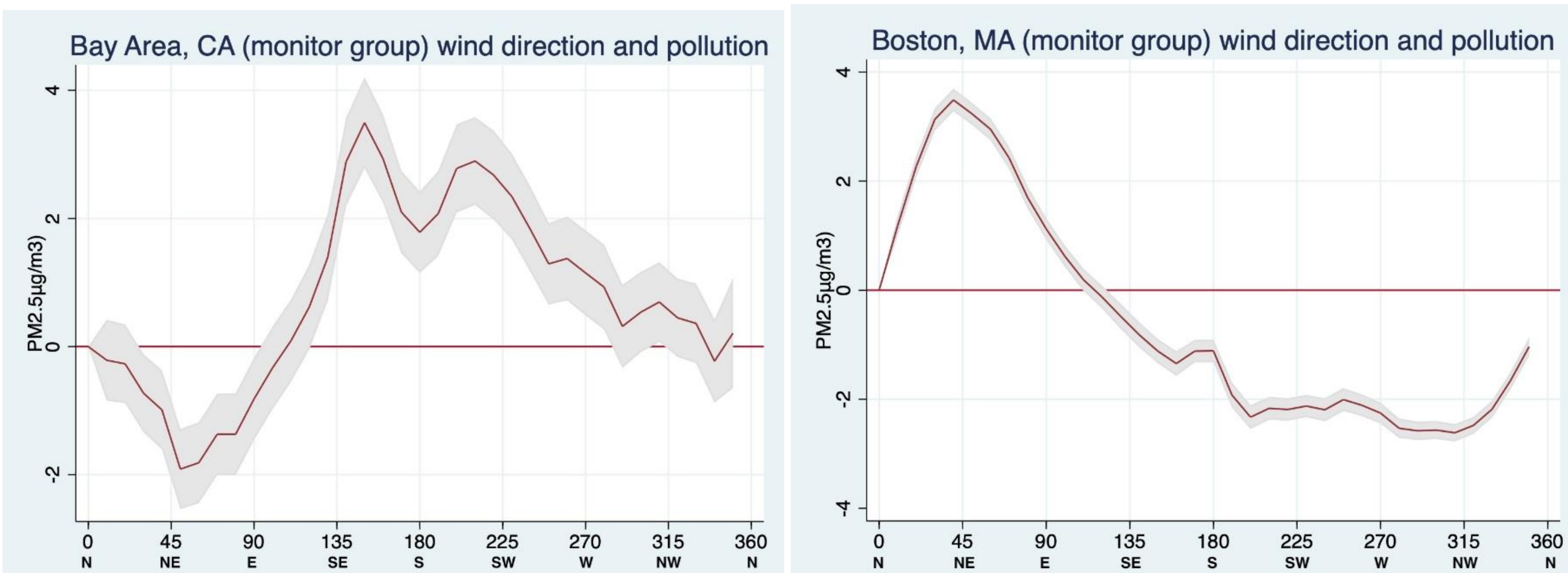
Notes: This figure shows the annual county mean of PM2.5 pollution over time. PM2.5 concentrations show some variety over the sample period.

Figure 2: Counties Assigned to 200 Monitor Groups



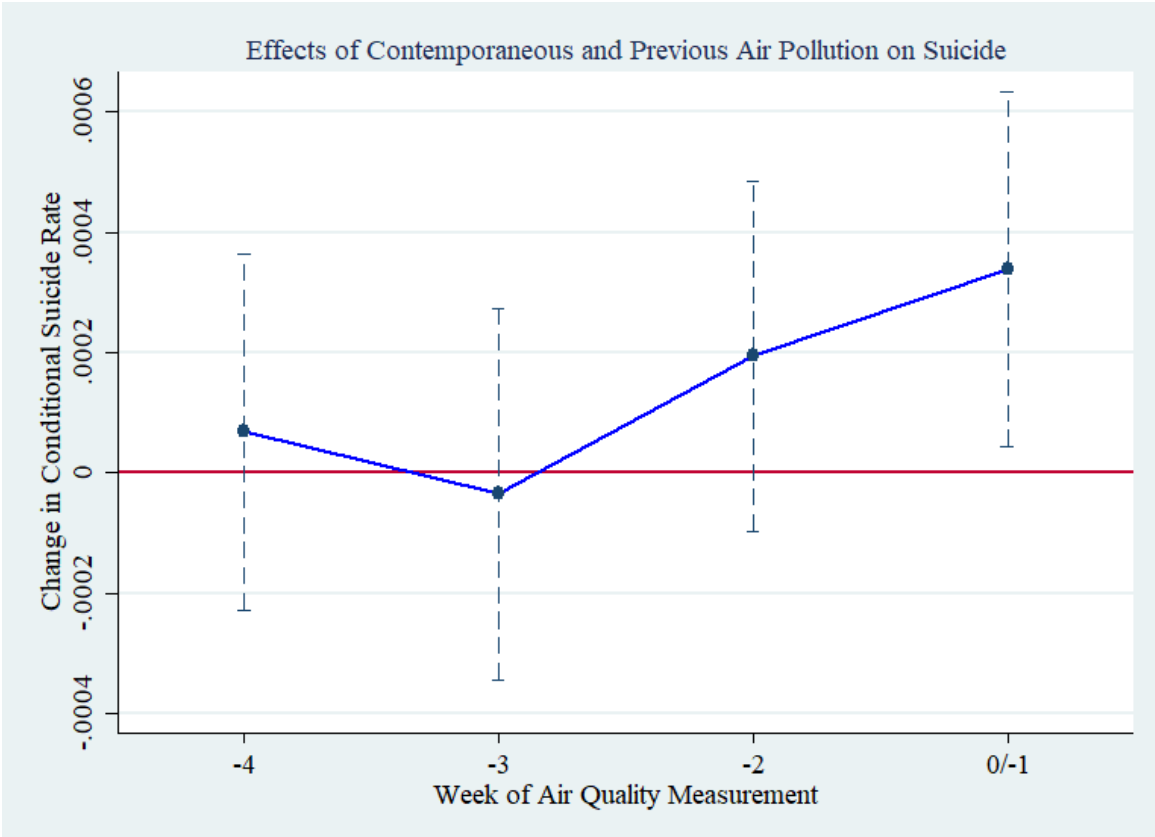
Notes: This figure depicts the 200 monitor groups in our sample, which comprises nearly every county in the entire United States.

Figure 3: Examples of wind direction and pollution exposure



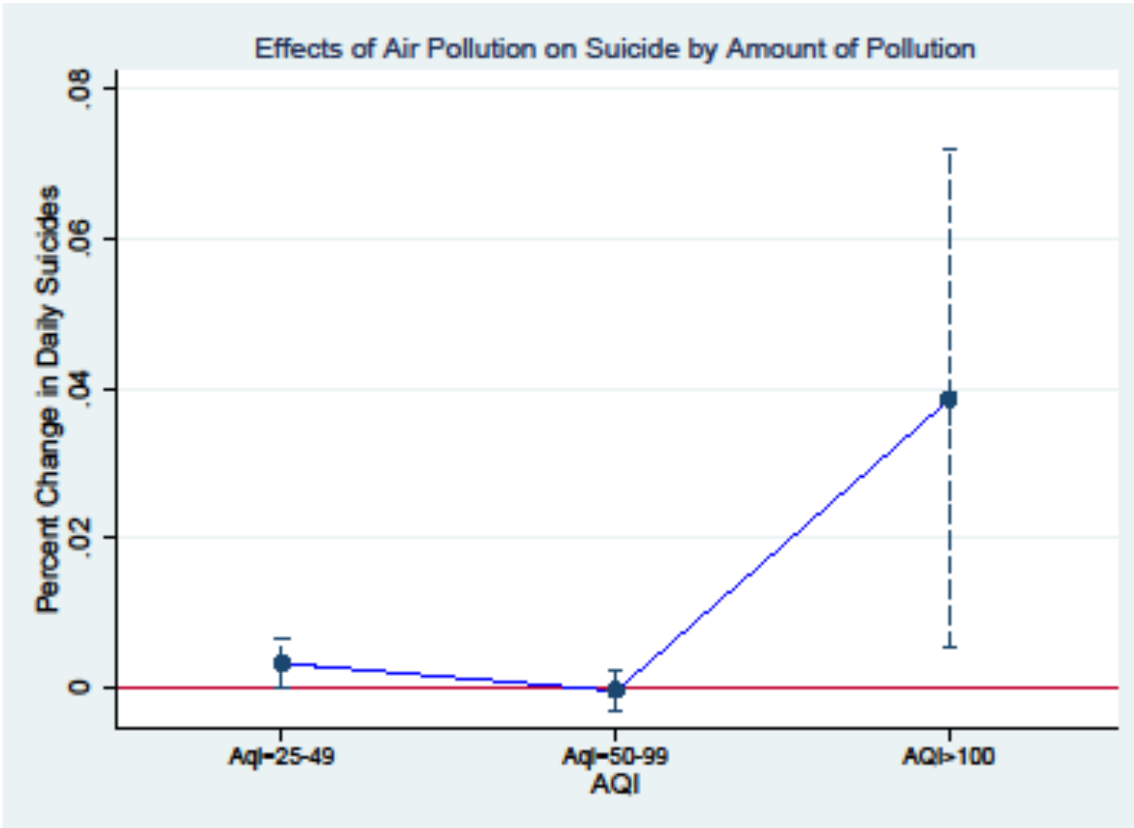
Notes: This figure depicts our first stage in two example monitor groups: the Bay Area and Boston. As shown, in some wind directions, average PM2.5 concentrations increase, and in others, they decrease. 95% confidence intervals depicted in gray.

Figure 4: 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/-1 is the week leading up to a suicide. We control for holidays, total population, average temperature, average precipitation, 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.

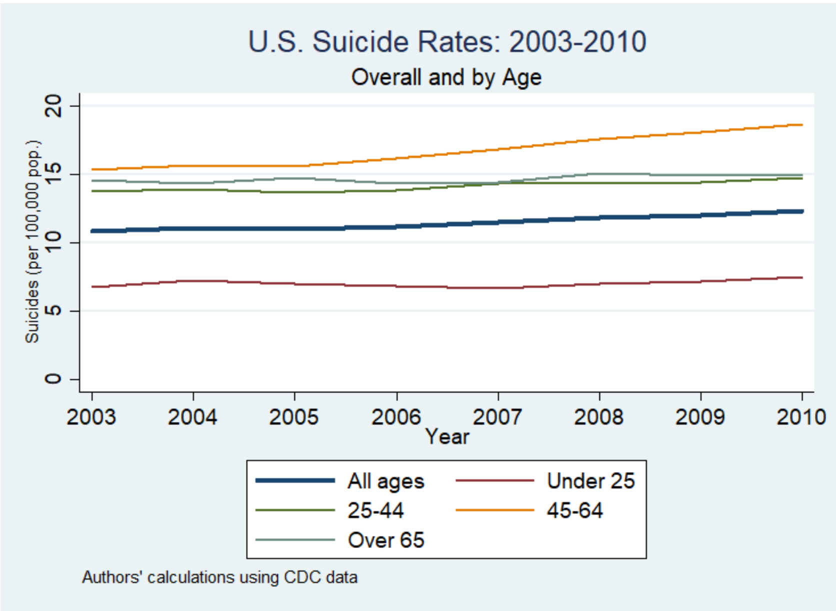
Figure 5: Effect of Air Pollution on Suicide by Amount of Pollution



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 FEs, holidays, total population, deciles of average temperature, and precipitation, wind speed, and unemployment rate. Vertical bars represent 95% confidence intervals based on standard errors clustered at the county level.

Online Appendix Tables and Figures

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



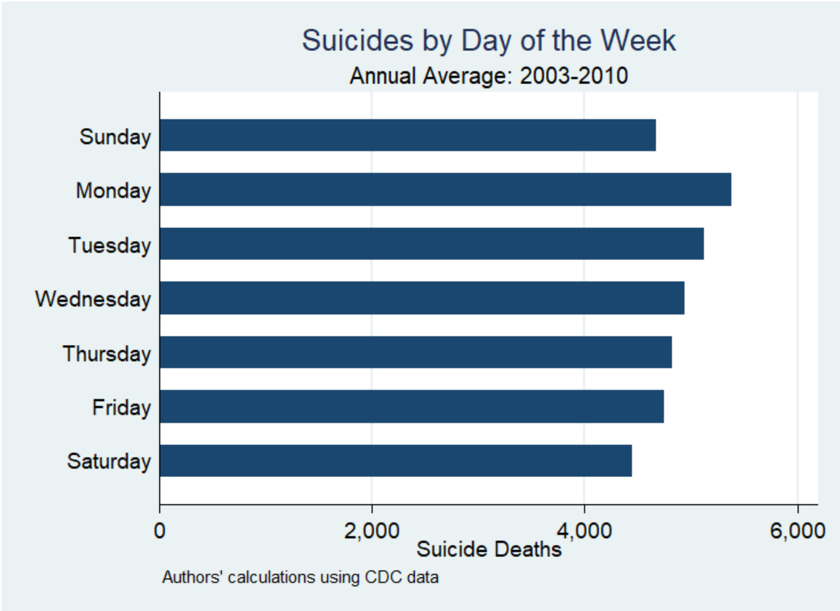
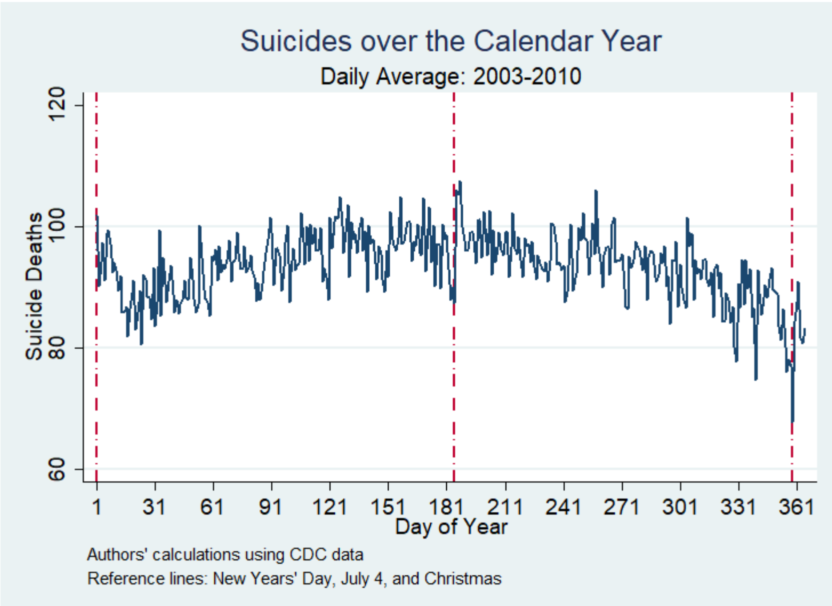


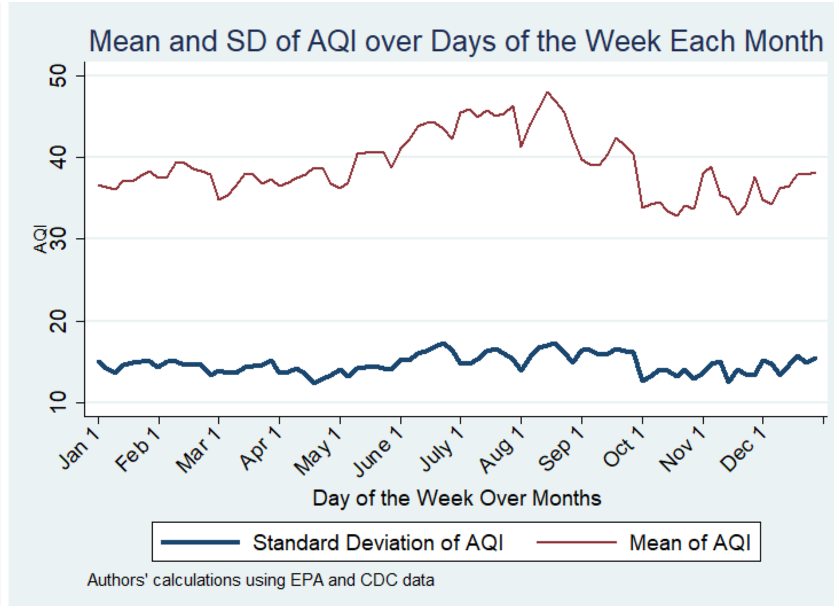
Figure 1A

Figure 1B

Notes: Figure 1A depicts trends in suicides by age over our sample's time period. Figure 1B 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.

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
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25.poll_cluster#0b.ang_range	1.833647***
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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
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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
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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***
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32.poll_cluster#90.ang_range	3.465375***
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32.poll_cluster#180.ang_range	1.527326***
	(0.076184)
32o.poll_cluster#270o.ang_range	0.000000
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	(0.100797)
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	(0.151257)

34.poll_cluster#180.ang_range	0.221907
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35.poll_cluster#0b.ang_range	2.276288***
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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
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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***
	(0.187136)
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
	(0.000000)
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
	(0.000000)
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
	(0.611011)
58.poll_cluster#180.ang_range	2.041855***
	(0.761479)
58o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
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
	(0.000000)
60.poll_cluster#0b.ang_range	1.664617***
	(0.129505)
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***
	(0.092631)
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
	(0.000000)
62.poll_cluster#0b.ang_range	1.240450***
	(0.086013)
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
	(0.000000)
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
	(0.000000)
65.poll_cluster#0b.ang_range	2.312312***
	(0.217036)
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***
	(0.312888)
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
	(0.000000)
67.poll_cluster#0b.ang_range	5.943604***
	(0.112441)
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
	(0.000000)
70.poll_cluster#0b.ang_range	-0.077965
	(0.137618)
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
	(0.000000)
71.poll_cluster#0b.ang_range	3.537330***
	(0.212764)

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
	(0.000000)
72.poll_cluster#0b.ang_range	3.100285***
	(0.327003)
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
	(0.000000)
73.poll_cluster#0b.ang_range	1.222237***
	(0.161482)
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***
	(0.084973)
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***
	(0.143336)
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
	(0.000000)
79.poll_cluster#0b.ang_range	1.003463***
	(0.197282)
79.poll_cluster#90.ang_range	0.699692
	(0.619295)
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**
	(0.213059)
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***
	(0.208244)
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***
	(0.138737)
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
	(0.452123)
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
	(0.000000)
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***
	(0.068780)
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
	(0.000000)
90.poll_cluster#0b.ang_range	-0.407911
	(0.368206)
90.poll_cluster#90.ang_range	0.141854
	(0.535802)

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***
	(0.151552)
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
	(0.000000)
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
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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
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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
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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
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117.poll_cluster#0b.ang_range	1.754653***
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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
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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
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120.poll_cluster#0b.ang_range	1.820096***
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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
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122.poll_cluster#0b.ang_range	4.145147***
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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
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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
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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***
	(0.080399)
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***
	(0.309621)

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***
	(0.121206)
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***
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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***
	(0.107497)
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
	(0.000000)
138.poll_cluster#0b.ang_range	0.066326
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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***
	(0.071106)
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***
	(0.112984)
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
	(0.000000)
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***
	(0.112354)

141o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
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***
	(0.102877)
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***
	(0.080167)
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
	(0.000000)
145.poll_cluster#0b.ang_range	0.304116
	(1.125558)
145.poll_cluster#90.ang_range	1.452138
	(1.494664)
145.poll_cluster#180.ang_range	1.625433*
	(0.887678)
145o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
148.poll_cluster#0b.ang_range	1.003240***
	(0.054729)
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
	(0.000000)
149.poll_cluster#0b.ang_range	2.369887***
	(0.095061)
149.poll_cluster#90.ang_range	1.796273***
	(0.141617)

149.poll_cluster#180.ang_range	0.871462***
	(0.109607)
149o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
150.poll_cluster#0b.ang_range	2.196984
	(1.672894)
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
	(0.000000)
151.poll_cluster#0b.ang_range	0.659729***
	(0.127488)
151.poll_cluster#90.ang_range	1.274982***
	(0.200912)
151.poll_cluster#180.ang_range	1.353439***
	(0.067696)
151o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
152.poll_cluster#0b.ang_range	-0.683034***
	(0.084643)
152.poll_cluster#90.ang_range	0.135930
	(0.198346)
152.poll_cluster#180.ang_range	0.477758***
	(0.073861)
152o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
154.poll_cluster#0b.ang_range	-0.635512***
	(0.181181)
154.poll_cluster#90.ang_range	-0.286976
	(0.316748)
154.poll_cluster#180.ang_range	0.061309
	(0.187285)
154o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
156.poll_cluster#0b.ang_range	4.259030***
	(0.139921)
156.poll_cluster#90.ang_range	5.900223***
	(0.150902)
156.poll_cluster#180.ang_range	1.590715***
	(0.129108)
156o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
157.poll_cluster#0b.ang_range	2.469101***
	(0.105871)

157.poll_cluster#90.ang_range	2.180887***
	(0.139376)
157.poll_cluster#180.ang_range	1.296182***
	(0.083416)
157o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
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
	(0.000000)
160.poll_cluster#0b.ang_range	0.961810***
	(0.086488)
160.poll_cluster#90.ang_range	2.749685***
	(0.096668)
160.poll_cluster#180.ang_range	1.485634***
	(0.050614)
160o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
161.poll_cluster#0b.ang_range	0.748096***
	(0.090668)
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
	(0.000000)
162.poll_cluster#0b.ang_range	-0.371181
	(0.312445)
162.poll_cluster#90.ang_range	0.862109**
	(0.385978)
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***
	(0.073693)
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
	(0.000000)

164.poll_cluster#0b.ang_range	-0.859730***
	(0.228303)
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
	(0.000000)
165.poll_cluster#0b.ang_range	-0.989570***
	(0.378597)
165.poll_cluster#90.ang_range	-2.167839***
	(0.546613)
165.poll_cluster#180.ang_range	-1.738329***
	(0.408502)
165o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
167.poll_cluster#0b.ang_range	-0.948229***
	(0.246683)
167.poll_cluster#90.ang_range	0.678972*
	(0.376550)
167.poll_cluster#180.ang_range	1.602315***
	(0.369782)
167o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
168.poll_cluster#0b.ang_range	1.251942***
	(0.333828)
168.poll_cluster#90.ang_range	2.546530***
	(0.223473)
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
	(0.103386)
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
	(0.000000)
170.poll_cluster#0b.ang_range	-0.802594*
	(0.456439)
170.poll_cluster#90.ang_range	-1.068181**
	(0.474840)
170.poll_cluster#180.ang_range	-0.278853
	(0.276670)

170o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
171.poll_cluster#0b.ang_range	0.891880***
	(0.158376)
171.poll_cluster#90.ang_range	-0.164091
	(0.242575)
171.poll_cluster#180.ang_range	0.693168***
	(0.102309)
171o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
172.poll_cluster#0b.ang_range	5.158632***
	(0.121542)
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
	(0.348384)
173.poll_cluster#90.ang_range	1.235310***
	(0.471148)
173.poll_cluster#180.ang_range	-0.054023
	(0.138268)
173o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
174.poll_cluster#0b.ang_range	0.298099
	(0.231944)
174.poll_cluster#90.ang_range	2.031254***
	(0.243236)
174.poll_cluster#180.ang_range	1.686156***
	(0.265483)
174o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
175.poll_cluster#0b.ang_range	0.162523
	(0.141091)
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***
	(0.074841)
176.poll_cluster#90.ang_range	3.667721***
	(0.084064)

176.poll_cluster#180.ang_range	2.646855***
	(0.059122)
176o.poll_cluster#270o.ang_range	0.000000
	(0.000000)
177.poll_cluster#0b.ang_range	-0.359044**
	(0.164306)
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
	(0.842528)
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
	(0.269227)
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. Therefore, our coefficient of interest is allowed to vary across geographic regions.