Air Pollution and Criminal Activity: Microgeographic Evidence from Chicago

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A growing literature documents that air pollution adversely impacts health, productivity, and cognition. This paper provides the first evidence of a causal link between air pollution and aggressive behavior, as documented by violent crime. Using the geolocation of crimes in Chicago from 2001-2012, we compare crime upwind and downwind of major highways on days when wind blows orthogonally to the road. Consistent with research linking pollution to aggression, we find air pollution increases violent crime on the downwind sides of interstates. Our results suggest that pollution may reduce welfare and affect behavior through a wider set of channels than previously considered.
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Air pollution harms human well-being in a number of ways. Pollution has adverse effects on adult and infant health in the short-run and long-run[1], reduces productivity and labor market participation[2], impairs short-run cognition and lowers test scores[3] and induces avoidance behavior[4]. This paper adds a new dimension to the literature on the adverse effects of pollution by providing quasi-experimental evidence that air pollution affects violent criminal activity, a behavior that is particularly costly from a societal perspective.

We study crime in the city of Chicago from 2001 to 2012. Our identification strategy exploits variation in pollution driven by daily changes in wind direction. We begin by illustrating the relationship between crime and pollution at the city-level, using wind direction as an instrument for pollution. Major industrial point sources, such as refineries, corn milling facilities and foundries, are

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[1] Schlenker and Walker (2016), Currie and Walker (2011), Beatty and Shimshack (2014), among others
[2] Hanna and Oliva (2015), Zivin and Neidell (2012)
[3] Lavy, Ebenstein and Roth (2014), Stafford (2014), Archsmith, Heyes and Saberian (2018)
[4] Ito and Zhang (2016), Moretti and Neidell (2011), Zivin and Neidell (2009)

located southeast and southwest of the city of Chicago. When the wind blows from those directions, ambient air pollution rises. Using wind-direction as an instrument, we find that air pollution increases violent crime, but not property crime, consistent with research from biology and medicine linking air pollution and aggression.

Although the city-level results provide suggestive evidence, credibly establishing a causal impact of pollution on crime faces several challenges. For example, existing research points to a relationship between weather (specifically temperature), aggression, conflict and crime.[5] As pollution is both seasonal as well as a function of ambient weather conditions, misspecifying the relationship between weather and crime would risk misattributing of the effect of temperature or other seasonal drivers of crime to ambient pollution.

To address this, we exploit the microgeography of pollution and crime in Chicago. Using the geocoordinates of the universe of two million serious crimes reported to the Chicago Police Department between 2001 and 2012, we focus on the five major interstates that transect the city: I-90, I-94, I-290, I-55 and I-57. Following a literature that exploits interstates and a major fixed source of air pollution[6] we estimate the causal effect of pollution on criminal activity by comparing crime on opposite sides of major interstates on days when the wind blows orthogonally to the direction of the interstate. As an example, I-290 runs due west from the Chicago city center to the suburbs of Oak Park and Berwyn. On days when the wind blows from the south, the pollution from the interstate impacts on the north side of the interstate, whereas when the wind blows from the north, the pollution impacts neighborhoods to the south. On days when the wind blows orthogonally to the interstate, we find that violent crime increases by 1.9 percent on the downwind side. The effects we find are unique to violent crimes – we find no effect of pollution on the commission of property crime.

In essence, this approach uses the upwind side of the interstate on a given day as a control for the "treated" downwind side on the same day. Because our analysis focuses on areas right next to particular interstates, the upwind and downwind neighborhoods likely face identical weather conditions and unobservable economic activity on a given day. This comparison helps us address the main threats to panel identification - omitted or misspecified variables correlated with both pollution and criminal activity - and is the major benefit of the microgeographic identification strategy that we adopt.

Our approach also allows for a set of supplementary empirical tests that support pollution as the mechanism. We find that the effect of being downwind is attenuated on days when the direction of the wind does not blow pollution exclusively to one side of the interstate. We also find that the marginal effect of being downwind declines with distance, consistent with the measurements of downwind pollution exposure from Karner, Eisinger and Niemeier (2010). And,

[5] See e.g., Hsiang, Meng and Cane (2011) and Ranson (2014)

[6] see e.g., Currie and Walker (2011) and Anderson (2019), among others

consistent with the hypotheses that the mechanism operates through contemporaneous exposure, we find evidence that: (1) contemporaneous treatment rather than lagged treatment matters, and (2) the impacts of exposure are greatest on days with moderate temperatures when individuals are most likely to face outdoor exposure.

Finally, our localized analysis allows us to construct placebo tests based on thirty placebo 'interstates' parallel to I-290. Estimating a treatment effect at each placebo interstate, we find that the downwind treatment estimate is maximized precisely at the latitude at which I-290 transects the Chicago. Finally, we offer an alternative identification strategy that compares sides of the interstates to itself, on the same day of the year in other years in which location faced either more or less downwind exposure. Although the source of variation and control group is different than the identification strategy comparing the upwind and downwind sides on a given day (and our city-level results), we find very similar estimates of downwind exposure and continue to find an effect on violent, but not property crime. The consistency of the city-level and interstate analyses lend credibility to the causal inference we draw from the evidence.

At this early point it is useful to make explicit how this paper fits into the nascent literature linking short-term air pollution to crime. There are three papers most pertinent for us. Bondy, Roth and Sager (2018) study crime in London. In their main specification they apply fixed effect methods to a panel of data organized city-ward by day. They report a positive correlation between the Air Quality Index (AQI) - a composite measure of air pollution based on multiple pollutants - in a ward on a given date and a range of both violent and non-violent crimes. More concretely a 10 increase in AQI is associated with a roughly 2% increase in overall crime. In a robustness exercise they use wind-driven variation in local AQI levels to bolster causal interpretation of their main results. Burkhardt et al. (2019) apply similar fixed effects methods to a US county by day panel. They find that a 10% increase in fine particulates ($PM_{2.5}$) is associated with a 0.14% increase in violent crimes, a 10% increase in ozone with a 0.3% increase. They find no relationship with non-violent crime. Lu et al. (2018) examine a nine-year panel of air pollution and crime in 9360 US cities. They estimate positive association between annual city-level violent and non-violent crime and a composite city-level measure of air pollution. In each of these studies the effect sizes on violent crime rates are similar in order of magnitude to those that we will develop.[7]

Our paper has clear implications for policy. First, the effect sizes we estimate, although modest in magnitude, translate to significant social costs. Properly accounting for the impacts of pollution on criminal behavior would in-

[7]Just as our analysis will identify effects of windborne pollution from roads in the aggregate, these studies are also best interpreted as exploring portmanteau pollution effects. Lu et al. (2018) and Bondy, Roth and Sager (2018) are both explicit in using a composite pollution metric, and while Burkhardt et al. (2019) include as regressors $PM_{2.5}$ and ozone they do not report results for other common pollutants, such as NOx, CO and particles of other sizes, often highly-correlated with those that they study.

crease our estimates of marginal external cost of air pollution and increase the optimal stringency of externality-correcting regulations or Pigouvian pollution taxes. Furthermore, our results suggest that air pollution might have much broader impacts on cognition and human behavior than previously considered, which would further increase the optimal Pigouvian tax on pollution. Finally, our work speaks to the growing literature documenting the importance of within-city variation in pollution on specific neighborhoods. In recent years, concerns about local variation in pollution exposure have resonated with policy makers - much of state and local policy related to "environmental justice" is motivated by a desire to address differential pollution exposure faced by particular demographic groups.

The roadmap for the rest of the paper is as follows. In Section 2 we summarize the existing literature in biology, medicine and psychology linking air pollution to aggressive behavior. Although this paper documents a causal effect of air pollution on violent crime, previous research highlights several possible channels that – individually or in combination – might underpin the causal relationship we estimate. We discuss data in section 3 and in section 4 provide suggestive city-level evidence. In section 5, we examine the micro-geography of criminal activity in Chicago proximate to major interstates. Section 6 discusses policy implications and section 7 concludes.

I. Research on Environmental Conditions and Aggression

There is a long history in criminology, sociology, and economics focused on the relationship between criminal activity and the environmental conditions. The relationship between ambient temperature and crime is well-documented. Ranson (2014) uses 50 years of monthly data across nearly 3000 U.S. counties and semiparametrically estimates a flexible relationship between crime and weather. He finds that violent crime increases approximately linearly with respect to ambient temperature.[8] Similar patterns arise when considering aggressive behavior at levels from the interpersonal to the societal and in countries around the world (Burke et al. (2009); Hsiang, Meng and Cane (2011); Hsiang, Burke and Miguel (2013)).Other documented environmental drivers of crime include rainfall, most commonly by impacting agricultural productivity (Iyer and Topalova (2014)) and ambient light (Doleac and Sanders (2015)).

In addition to the three recent papers outline above, an older literature provides correlational evidence of association between short-run air pollution and interpersonal conflicts and adverse psychological outcomes. Rotton and Frey (1985) finds higher ozone levels in Dayton, Ohio are related to increased domestic disturbance calls and assaults, though the latter is not statistically significant. Research has also documented a positive correlation between air pollu-

[8] Cohn and Rotton (1997) and Jacob, Lefgren and Moretti (2007) provide similar evidence, that violent crime increases with temperature, and decreases with precipitation.

tion and adverse psychological outcomes. Rotton and Frey (1984) uses data on psychiatric emergencies from the Dayton police department and finds that such calls are positively correlated with levels of ozone precursors and sulfur dioxide, even when controlling for time trends and contemporaneous weather conditions. Szyszkowicz (2007) documents a similar positive correlation between emergency department visits for depression and ambient levels of a variety of pollutants, including CO, NO_2, SO_2, ozone, and $PM_{2.5}$. Further, there are several studies that find a positive association between levels of air pollution pollutants and suicide, suicide attempts, and suicidal ideation and psychiatric admission rates (Lim et al. (2012); Szyszkowicz et al. (2010); Yang, Tsai and Huang (2011); Briere, Downes and Spensley (1983); Strahilevitz (1977)). To our knowledge, there are no studies focusing on long-run exposure to air pollution, although Reyes (2007) exploits the staggered phase-out of leaded gasoline in the United States and finds that childhood lead exposure increases a cohort's future crime rate.

In this paper, we remain agnostic on the underlying mechanism (or mechanisms). However, previous research in medicine, biology and psychology identify several pathways by which pollution exposure might affect aggression. The first, and perhaps most straightforward, is that pollution might manifest in physical discomfort.[9] A long literature in psychology summarized by Anderson and Bushman (2002) documents a link between physical discomfort and aggressive behavior. Most relevant to our work, Rotton (1983) and Rotton et al. (1978) found laboratory exposure to malodorous reduced subject cognitive performance, tolerance for frustration, and the subjects' ratings of other people and the physical environment.[10] A second documented pathway linking pollution and aggression is that air pollution may directly affect brain chemistry by lowering levels of serotonin. Serotonin is a neurotransmitter that acts an a inhibitor. Low levels of serotonin are associated with increased aggression and impulsivity in adults, children and animals.[11] Krueger, Andriese and Kotaka (1963), Paz and Huitrón-Reséndiz (1996), González-Guevara et al. (2014) and Murphy et al. (2013) provide observational and experimental evidence linking short-term pollution exposure (specifically ozone) to decreased serotonin in animals. Third, Levesque et al. (2011); Van Berlo et al. (2010) find that air pollutants can inflame of nerve tis-

[9]Ambient air pollution exposure is known to manifest in physical discomfort. For instance, Nattero and Enrico (1996) followed 32 subjects over the span of nine months and found that high concentrations of ambient CO and NO_x were both significantly correlated with incidence of headache.

[10]Physical discomfort is also a central hypothesized mechanism for the link between high temperatures and aggression, both in the laboratory (Baron and Bell (1976)) and in the field (Ranson (2014)).

[11]Coccaro et al. (2011) summarizes the literature linking serotonin depletion and impluse control. Decreased serotonin is associated with an increased tendency to fight amongst rhesus monkeys (Faustman, Ringo and Faull (1993)), increased impulsive aggression in children (Frankle et al. (2005)) and decreased harm avoidance in adults (Hansenne et al. (1999)). In an experimental study, Crockett et al. (2013) finds "serotonin-depleted participants were more likely to punish those who treated them unfairly, and were slower to accept fair exchanges". In their summary of the human subject literature, Siegel and Crockett (2013) note that "...a meta-analysis encompassing 175 independent samples and over 6,500 total participants reveals a reliable inverse relationship between serotonin and aggression".

sues in humans, dogs, mice and rats. Rammal et al. (2008) finds experimental evidence that oxidative stress and similar neuro-inflammation increases aggression in mice, specifically the frequency with which mice attack unfamaliar mice put into their space. Finally, pollution may lead to other physiological changes that manifest in increased aggression. Maney and Goodson (2011) surveys the literature on the role played by *hormonal* mechanisms in animal aggression. Uboh et al. (2007) provides experimental evidence causally-linking exposure to gasoline vapors to substantially-elevated levels of testosterone in male rats. Testosterone is itself linked to violent crime in humans (Dabbs Jr et al. (1995); Birger et al. (2003)).[12]

II. Data

Our crime data come from administrative records documenting all crimes reported to the Chicago police department between 2001 and 2012. We obtain crime data from the Chicago Police Department's Citizen Law Enforcement Analysis and Reporting system, accessed using the City of Chicago's open data portal.[13] For each reported crime, the dataset reports the type of crime, date, time of day, latitude and longitude of the address at which the crime was reported and other details of the incident (e.g., whether an arrest was made, whether the crime was considered domestic).

To narrow our focus to commonly-examined crimes, we restrict the sample to the *two million* FBI Type I crimes reported in the city of Chicago between 2001 and 2012, including: homicide, forcible rape, robbery, assault, battery, burglary, larceny, arson, and grand theft auto. As some types of serious crime are infrequent, we aggregate these crimes into violent crimes (homicide, forcible rape, assault and battery) and property crimes (burglary, robbery, larceny, arson, and grand theft auto). The 240,000 violent crimes are predominately battery (57%) and assault (32%), while the 1.8 million property crimes are predominately larceny (58%), burglary (17%) and grand theft auto (14%).[14]

As in many locations, crime in Chicago declined over the 2001-2012 study period and exhibits substantial seasonality and within-day variation. We document these patterns in the appendix.[15] The time stamp of each crime reflects the

[12]As another example, carbon monoxide may directly affect physical and cognitive functioning by binding to hemoglobin, and reducing the oxygen-carrying capacity of the cardiovascular system. This oxygen deficiency can have deleterious effects on an exposed individual. In a rare controlled experiment, Amitai et al. (1998) exposed 45 Hebrew University students to various levels of carbon monoxide and found that low level exposure impaired learning, hindered attention and concentration, and slowed visual processing.

[13]https://data.cityofchicago.org/

[14]We only observe crimes reported to the Chicago police department. Crimes may be differentially underreported, especially those that are personally sensitive. However, unless underreporting is correlated with wind-driven pollution levels, underreporting will not bias our estimates.

[15]Figure A.3 presents the annual trends in property and violent crimes between 2001 and 2012. Each type of crime's 2001 level is normalized to 100. Overall, violent crime has declined more rapidly than property crime, although both varieties are far below their 2001 levels. Figure A.2 plots the seasonality of crime in Chicago - both violent crime and property crime increase during the summer months. Criminal activity also cycles over the course of each day - Figure A.1 shows that crime peaks during evening hours.

time at which the crime was reported, rather than committed. This might result in some degree of misreporting in terms of the hour (more likely) or the date (less likely). Consequently, we focus on daily variation in crime and pollution and aggregate crimes to the daily level.

The geographic patterns of property versus violent crime also differ. The heat maps in Figure A.4 plot the density of property and violent crime throughout Chicago for 2001-2012. The grey lines denote the major interstates running through the city limits. The shades are comparable only within a map; that is, an area on the violent crime map that is darker than an area on the property crime map does not necessarily indicate that there are more violent crimes in absolute terms. Rather, the *share* of violent crimes that occur in that area is greater than the share of property crimes. Less affluent locations, such as the South Side, and the westernmost portions of Chicago experience higher rates of violent crime. Although these areas also experience high rates of property crime, downtown Chicago experiences higher rates of property crime.

The temporal, seasonal, and geographic distributions of crime nicely summarize some of the identification challenges that we face. First, crime and pollution have both been declining over time in Chicago. Thus, we focus on short-run variation for causal identification. Second, seasonality of pollution and crime suggests that weather (particularly temperature) is an important confounding variable. Third, geographic variation in crime stresses the importance of an identification strategy to address unobservable economic activity.

To control for weather conditions, we use data from the National Climatic Data Center (NCDC). The NCDC is the most comprehensive source of publicly available U.S. weather data, reporting temperature, precipitation and other meteorologic variables at approximately 10,000 locations. For the analysis, we use temperature, precipitation, wind speed and wind direction at Midway airport, the closest weather station to the Chicago city center consistently reporting all four variables.[16] As we are aggregating our crime data to the daily-level, we construct a measure of the average wind vector over the course of a day from hourly data. We construct similar summary statistics for available covariates correlated with crime, such as daily maximum temperature and precipitation. Table 1 presents the means and standard deviations of our relevant empirical variables.

III. City-level Crime and Pollution

We start by establishing a suggestive relationship between pollution and crime at the city-level using a time-series variation. In Chicago, day-to-day variation in is partially driven by major industrial point sources located to the southwest and southeast of Chicago, including the Blue Island refinery and Arcelor Mittal

[16]As a comparison, we also examined similar variables at O'hare, located approximately twice as far from the city center as Midway airport. Readings at Midway and O'hare for all four variables are highly correlated. Correlation in temperatures, precipitation, wind speed and wind direction were 0.995, 0.750, 0.950 and 0.703. Our results throughout the paper are not sensitive to the choice of weather station.

steel mill to the southeast and the ExxonMobil Joliet refinery, the Citgo Lemont refinery and the Corn Products International wet corn milling operation to the southwest. Due to the coverage of monitors in Chicago over the study period, we focus on PM_{10} readings, recognizing that PM_{10} emissions act as a proxy for many industrial pollutants.[17] As an illustration of our identification strategy, Figure 1 plots the relationship between wind speed, wind direction and pollution at a specific PM_{10} monitor in Chicago.[18] The shade of the plot region represents mean pollution intensity, the arc direction represents the average direction *from which* the wind is blowing, and the distance from the center of the circle represents vector-based wind speed. As the figure illustrates, when winds originate from either the southeast or southwest, the monitor reports elevated PM_{10} levels. In contrast, when the wind originates from the direction of Lake Michigan, PM_{10} concentrations are lower.

Our empirical strategy is relatively straightforward. To address seasonality and disparities between the weekdays and weekends, we include a set of calendar fixed effects, including month-of-year fixed effects, day-of-week fixed effects and dummy variables corresponding to holidays and the first day of each month. To address the correlation of both pollution and crime with weather conditions, we flexibly condition on temperature and precipitation using a semi-parametric bin estimator for both and include other weather observables (e.g., sky cover, dew point and barometric pressure). Finally, to address unobservable economic activity, we instrument for pollution using wind direction, exploiting the fact that when winds originate from the southeast or southwest, monitors in Chicago report elevated pollution levels. In this case, the identification strategy is similar spirit to that of Schlenker and Walker (2016), who use wind direction and airport emissions to instrument for ambient pollution in California to estimate causal health effects. Hence, the relevant exclusion restriction is that there are no omitted variables correlated with both crime and wind-direction, after conditioning on fixed effects and weather covariates. As an example, this might be violated if after conditioning on weather and fixed effects, winds off of Lake Michigan affect people's moods in a way that lowers violent crime. In this case, we might misattribute a "Lake Michigan" effect on crime to pollution.

Formally, we estimate the following 2SLS specification:

$$Poll_t = \alpha W_t + \beta X_t + \epsilon_t \tag{1}$$

$$ln(Crime_t) = \gamma X_t + \lambda \widehat{Poll}_t + \nu_t \tag{2}$$

W_t includes daily average wind direction in 20-degree bins. X_t is a vector

[17]Our direct measures of ambient pollution come from the Environmental Protection Agency's network of monitors. We use 24-hour averages provided by the EPA. To avoid composition problems, we only include days for which all the PM_{10} monitors have a valid daily average.

[18]For reference, monitor 31-1016-3 is located in the city limits, approximately twelve miles southeast of the city center.

of controls including 5°C daily maximum temperature bins, daily precipitation, vector-based average wind speed, binned dew point, barometric pressure and average sky cover, and a set of calendar fixed effects, including a first of month indicator, a January 1 indicator, holiday indicators, day of week dummies, and month of sample dummies. The set of controls also includes the average maximum daily temperature over 1991 - 2000 matched by day-of-year to the study sample as an additional control for seasonal variation in temperature.[19] $Poll_t$, is the average daily PM_{10} across all PM_{10} monitors in the city of Chicago, standardized so that a unit change in the variable is equal to a one-standard deviation increase ($14.4\mu g/m^3$). Our dependent variable $Crime_t$ is the log of the total number of violent or property crimes in Chicago on day t. To allow for serial correlation in weather and criminal activity, we report Newey-West standard errors in all specifications.

Table 2 displays the results from the city-level regressions. Columns 1 through 3 present the results using violent crimes as the dependent variable. Column 1 presents the results from an OLS regression of violent crime on pollution and calendar fixed effects. Column 2 adds weather controls and historical mean temperature matched by day-of-year. Column 3 presents the IV estimates, using wind direction as a first-stage excluded instrument for pollution. As suggested by Figure 1, the first stage is quite strong - the F-statistic is 26.4.

Column 1 highlights one of the identification challenges we face with estimating an effect of pollution on crime, specifically, the strong correlation between weather, pollution and criminal activity. Including calendar fixed effects but not weather controls, we estimate a one-standard deviation increase in PM_{10} emissions is associated with a 6 percent increase in violent crime. But, the estimate conflates a potential effect of pollution with the effect of weather. PM_{10} pollution and temperature are positively correlated, as are temperature and criminal activity. Adding flexible weather covariates in column 2 reduces the coefficient on PM_{10} pollution by roughly eighty percent. Column 3 presents the IV estimates, using binned wind-direction as a first-stage instrument. Using this specification, we estimate a one-standard deviation increase in PM_{10} emissions is associated with a 2.9% increase in violent crime. As a point of reference, the estimated effect of moving from the 77-86°F / 25-30°C maximum temperature bin to the 86-95°F / 30-35°C bin is a 7% increase in violent crime.[20]

Consistent with the medical literature on pollution and aggressivity, the effect seems to be specific to violent crime. In columns 4 through 6, we replicate the specifications in columns in 1 through 3, using property crimes. In column 4, in which we omit weather controls, we find a positive relationship between pollution and property crime. But, this positive estimate is biased upwards by

[19] See, e.g., http://datacolada.org/46.

[20] Again, a bit of cautious interpretation of our estimate is necessary. As we note above, PM_{10} readings are an observable proxy for industrial air pollution that likely is a mix of a air pollutants. We have also run specifications that expressly condition on co-pollutants and find qualitatively similar results.

the omission of weather covariates. Once we control for weather covariates in columns 5 and 6, the coefficients on pollution are close to zero, and although insignificant, relatively precisely estimated.

We focus on more serious, part 1 crimes in this paper. These crimes entail greater societal costs and are more likely to be reported to police than less serious offense. Never the less, we extend the analysis above to less serious, non-part 1 crimes reported to the Chicago police department. Simple assault and simple battery, which typically involve minor injuries and less serious circumstances, make up the vast majority on violent crimes not classified as Part 1. Non-part 1 non-violent crimes include drug possession, prostitution, vandalism and other less serious offenses. Table 3 reports the results from the IV specification for violent and non-violent, part 1 and non-part 1 crimes. Columns 1 and 4 recreate the IV results from Table 2, while Columns 2 and 5 examine similar specifications for non-part 1 violent and non-violent crimes, respectively. Finally, columns 3 and 6 present results for the log of all crimes. Although magnitudes are slightly more modest, we find evidence that the number of less serious violent crimes also increases on days where wind-driven pollution impacts air quality. A one-standard deviation increase in PM_{10} emissions is associated with a 1.4% increase in less serious violent crime and a 1.7% increase in violent crime in the aggregate. As for more serious property crimes, we do not find a strong relationship between the commission of less serious non-violent crimes and wind-driven air pollution.

These city-level regressions provide suggestive evidence of a causal relationship between ambient air pollution and violent crime. Yet, they are identified entirely off of time-series variation. If we fail to control for unobservables correlated with both wind direction and crime or mis-specify the true relationship between the dependent variable and crime-related observables, we may make incorrect inferences about the causal relationship between pollution and criminal activity.

IV. Microgeographic Evidence

To provide more compelling causal evidence, we exploit the fact that we know the specific location of each crime reported to the Chicago police. This allows us to estimate the relationship between pollution and crime by comparing local neighborhoods as they are differentially impacted by pollution. Rather than impute pollution between monitors or predict pollution from an air transport model, we use major interstate highways radiating from the center of the city as fixed sources of pollution. We examine crime in neighborhoods on either side of an interstate highway on days when the wind blows orthogonally to the direction of the interstate.

When the wind blows "across" the highway, the pollution generated from vehicles disproportionately impacts the downwind neighborhood. To demonstrate that pollution from interstates can meaningfully impact air quality, consider Figure 2 which summarizes CO readings at one of the monitors in Chicago. This monitor (31-6004-1) is located immediately north of the I-290 interstate, which runs straight west from the Chicago city center to the suburbs of Oak Park and Berwyn. Like Figure 1, the shade of the contour plot denotes mean CO pollution reading at the monitor as a function of vector-based net wind speed and direction. The vector and distance from the origin denote the direction *from which* the wind is blowing and the average wind speed, respectively. For this particular monitor, the concentration of CO is greatest when the wind blows from the highway toward the monitor. Since the area on the south side of the highway (immediately across from the monitor) is open space[21], we attribute the incremental pollution at the monitor when the wind is blowing from the south to the pollution from traffic on I-290. This approach allows us to employ a treatment-control framework, where on a given day, the downwind location is "treated" by pollution. The advantage of this approach is that the very local nature of the exercise allows us to use the upwind neighborhood as a control that faces identical weather conditions, plausibly addressing potential concerns with mis-specification or omission of correlated weather variables. Furthermore, since the interstates in Chicago run in different directions, different neighborhoods are "treated" each day. This helps address the identification concerns with more aggregate analyses that might confound causal identification of the impact of pollution on crime.[22]

Our identification strategy is easiest to illustrate using I-290 as an example. To causally estimate the effect of pollution on crime, we compare crimes along the north side of I-290 to the south side of I-290 on days when the wind is blowing orthogonally to the interstate. On a day when the wind is blowing from the south, the pollution impacts the north side of I-290 and vice-versa. In essence, the side of the interstate from which the wind is blowing acts as a control for unobservable daily variation in side-invariant criminal activity, driven by, for example, weather. For our estimate to be biased, an omitted variable must differentially affect crime on the side of the road to which the pollution is blowing.

We extend this approach to include neighborhoods within one mile of other interstates in the Chicago area, plotted in the map in figure 3.[23] The figure plots the locations of all crime within one-mile of the interstates, marked in red. We further limit the sample of crimes to the colored regions in Figure 3 based on several criteria. First, we drop crimes that are within one mile of more than

[21]Forest Home Cemetery covers an area roughly three-quarters of mile east-west and half mile north-south on the side of I-290 immediately opposite from the pollution monitor.

[22]Barrios et al. (2012) highlight the importance of accounting for spatial correlation beyond the level at which the treatment is assigned. Unlike the context they examine, where inference is based on individual level outcomes and state-level treatments, the downwind treatment varies at the same level as our unit of observation (the interstate-side-day level).

[23]We select the one mile boundary to be inclusive of the region likely affected by downwind exposure to an interstate. Karner, Eisinger and Niemeier (2010) presents observational evidence that downwind exposure decays with distance, reaching background pollution levels within roughly one half a kilometer for NO_x and a kilometer for PM2.5.

one interstate. In these areas, a control region upwind of one interstate may be downwind from a second interstate. excludes crime in downtown Chicago (where the major interstates converge) and crime close to the interchanges of I-90, I-94, and I-57, both north and south of the city. Second, we drop crimes in the extreme northwest and southeast of the city. The northwestern region is proximate to O'Hare International Airport. While the airport is technically part of the City of Chicago, it is connected to the rest by only a narrow strip of highway, and is unlikely to be representative of criminal activity elsewhere. The southeastern part of the city borders Lake Michigan to the east and Lake Calumet to the southwest; limiting the extent of activity on the waterfront sides of I-90 and I-94. Finally, we exclude crimes on the western edges of I-55 and I-290. Westward of 87.74 W longitude, I-55 exits (and then re-enters) the city and I-290 runs along the city limits as we only possess information about crimes reported within the Chicago city limits.

Finally, we focus our analysis on days during which one side of the interstate is strongly treated. In our main set of results, we consider the sample of interstate-segments-days for which the average wind direction on a given day was within sixty degrees of the line orthogonal to the direction of the interstate.[24]

Our main specification regresses the number of crimes on side s of interstate i on day t on interstate-side FE, interstate-date FE and a dummy variable equal to one if side s is the side downwind from interstate i on day t. In most of our specifications, we normalize the number of crimes by the mean, so as to be able to interpret the coefficient estimates as the effect of downwind exposure in terms of the percent of average crime.[25] Formally,

$$Crime_{ist} = \alpha_{is} + \gamma_{it} + \beta Downwind_{ist} + \epsilon_{ist}. \tag{3}$$

Because the nature and motivation of violent and property crimes differ, we separately estimate the relationship for the two classes of crimes. Interstate-side fixed effects (α) control for time-invariant unobservables that are correlated with criminal activity on each side of the interstate. The interstate-date fixed effects (γ) control for daily variation in criminal activity near each interstate. Since treatment status of a given side of an interstate varies daily, we report robust standard errors in all specifications. [26]

One concern for identification is that an interstate generates other disamenities that might confound our results. One note of particular concern is that vehicles emit both noise and physical air pollutants, both of which have been linked to changes in emotional state and tendency to aggressivity in ways that might drive

[24]Appendix figure A.7 illustrates how we classify upwind and downwind interstate segments.

[25]We also present estimates using the number of crimes and a Poisson count model in Appendix Table A.1. The results are qualitatively identical.

[26]In appendix table A.2, we also calculate Newey-West standard errors, errors clustered by interstate-side-month and errors clustered by interstate-side-year. We find little evidence that robust standard errors overstate our statistical precision as a result of serial correlation.

increases in crime. For example, Hener (2019) provides evidence of a causal effect of aircraft noise on the rate of physical assaults in the area surrounding Frankfurt airport.[27] However, the use of the upwind side of the road as a control allows us to address this concern, given well-established research documenting that the dispersion of traffic noise is largely insensitive to wind patterns in urban environments. Shu, Yang and Zhu (2014) measures noise pollution in the vicinity of two major freeways in Los Angeles, and finds that "residents who live on the dominantly downwind side are exposed to ... similar noise level when compared to the residents who live on the upwind side" (page 137). Weber (2009) finds that the spatial distribution of noise measured across different days in the vicinity of major roads in Essen, Germany was invariant to wind direction. Allen et al. (2009) repeatedly measured noise at sixty-nine sites within 500 m of major roads in Chicago and forty-six in Riverside County, CA under varying wind conditions. The rate of decay of noise with respect to distance upwind from roads was not significantly different from that on the downwind side, leading the authors to conclude that while concentrations of the physical air pollutants - which they also monitored - were wind-sensitive, "(I)n contrast, noise had similar distance decay relationships upwind, and the similarity of 5-minute noise measurements made ... in different seasons (and with different wind characteristics) provides further evidence that noise is minimally impacted by wind direction" (Allen et al. (2009) at page 341)).[28]

A. Results

We present main results for violent crime (Panel A) and property crime (Panel B) in Table 4. Columns 1 and 2 report the effect without the inclusion of route-side and route-day fixed effects. Column 3 corresponds to the specification in equation (3).

Focusing first of violent crime in Panel A, moving column 1 to column 2, we find that the omission of route-side fixed effects positively biases the estimate of the downwind treatment effect, consistent with the predominately-downwind side of the interstate experiencing a higher rate of violent crime irrespective of wind direction. Controlling for both route-side and route-day fixed effect, we find that violent crime increases by about 1.9% on the downwind side of the interstate.

A remaining threat to identification arises if we omit a variable correlated with wind direction that differentially affects crime on one side of the interstate. Us-

[27] While Hener exploits plausibly-exogenous variations in wind direction as part of his identification strategy this is not because noise is itself wind-carried. Rather safety rules regarding aircraft movements in the European Union cause switches between westbound and eastbound approach landings at Frankfurt airport in response to changes in wind conditions. This varies the set of surrounding communities under the flight-path and therefore 'treated' to noise at any given time.

[28] This is echoed by the Traffic Noise Model (TNM) required by the Federal Highway Administration for traffic noise studies that doesn't explicitly model prevailing wind-direction for simulating the road noise impacts and by other papers examining the downwind impacts of roadways (e.g., Anderson (2019)).

ing I-290 as an example, suppose that the wind only blows from the south on hot summer days and houses on the north-side of I-290 are much less likely to have air conditioning than houses on the south-side of I-290. We might observe a relative increase in crime on the north-side of the I-290 when the wind is blowing from the south due not to pollution, but rather to increased exposure to high temperatures.

This seems a unlikely threat to identification. The seven interstate segments we examine transect different parts of the city of Chicago with different socioeconomic characteristics. Furthermore, the interstate segments travel in different directions. To bias our estimates, such a story would have to hold for different regions of the city with different demographics, some of which are east and west of an interstate and some of which are north and south of an interstate. Nevertheless, we can address the concern directly, by allowing the number of crimes on each of the fourteen interstate sides to vary independently with temperature and precipitation. Conceptually, this identifies the downwind effect by comparing the number of crimes on opposite sides of an interstate on days with identical weather conditions, but days that differ with respect to wind direction. Formally, we estimate

$$Crime_{ist} = \alpha_{is} + \gamma_{it} + \beta Downwind_{ist} + \Lambda_{is} X_{ist} + \epsilon_{ist}. \tag{4}$$

where X_{ist} includes the maximum temperature over the course of the day and precipitation over the course of the day and present the estimates in column 4.

We find little evidence that these additional controls explain our results in column 3. When we allow for criminal activity on the each side of the road to vary independently with temperature and precipitation, our estimates are almost identical: violent crime increases by roughly 1.9% on the downwind side, relative to mean levels of violent crime.

Panel B of Table 4 presents the results of identical specification for property crime rather than violent crime. As in the city-level regressions, we find no evidence that pollution impacts property crime. Although our estimates are indistinguishable from zero, they are relatively precisely estimated, suggesting little relationship between pollution and property crime.

EFFECTS BY SUBCATEGORY OF VIOLENT CRIME. — Although in our main specification we aggregate violent crimes, violent crimes differ substantially with respect to their nature and cost. In addition, violent crimes escalate in severity, specifically aggravated assault and aggravated battery. An assault is characterized by the threat of bodily harm, defined as "an unlawful attack by one person upon another wherein the offender displays a weapon in a threatening manner, placing someone in reasonable apprehension of receiving a battery," whereas battery is the infliction of bodily harm, defined "an unlawful attack by one person upon another wherein the offender uses a weapon or the victim suffers obvious severe or aggravated bodily injury involving apparent broken bones, loss of teeth, possible internal injury, severe laceration, or loss of consciousness."[29]

In table 5, we estimate effects for the individual violent crimes. To directly compare the coefficients, our specification uses the number of crimes (rather than crimes as a percentage of mean crime levels) as the dependent variable.[30] We find evidence that the aggregate increase in violent crime from downwind exposure masks an increase in reports of aggregated battery offset by a *decrease* in aggregated assaults. One interpretation of these results is that pollution causes a net increase in violent crime, but it also results in marginal assaults escalating into batteries. While the coefficient on murder and forcible rape are positive, the effects on both are less precisely estimated.

B. Supporting evidence of wind-driven pollution

One advantage the micro-geographic analysis is we can examine whether the estimate of the treatment effect varies in a way consistent with downwind pollution exposure as the mechanism. To begin, we examine how the estimated treatment effect varies with the two sample restrictions that underpin the results in Table 4. When constructing the sample for the main results, we limited the sample to days when during which the average wind vector over the course of the day was within 60 degrees of the vector orthogonal to the direction of the road. If the criterion for inclusion is less strict, (i.e., the angle is greater than 60 degrees), an side of an interstate might be classified as "treated" on days with less intensive downwind exposure. Such inclusion would tend to attenuate the treatment effect. [31]

The second sample restriction is the distance on either side of an interstate we consider when counting the number of crimes. In our main results, we include crimes within one mile of either side of the interstate. But, observational evidence in Karner, Eisinger and Niemeier (2010) suggests downwind pollution exposure decays with distance, reaching background levels for most pollutants within a kilometer.[32] In our context, if pollution is the driving mechanism, we should expect the marginal effect to decreases with distance to the highway.

Table 6 presents the results of estimating the specification from column 4 of table 4 as we vary the inclusion restrictions. Here, we use the number of crimes as our dependent variable so as to direclty compare the downwind impacts in levels across different inclusion restrictions. Each cell reports the estimated treat-

[29]Definitions of FBI index crimes are given at http://gis.chicagopolice.org/clearmap_crime_sums/crime_types.html.

[30]We present a similar table for property crimes in the appendix as table A.7. As with our aggregate results, we find little evidence that subcategories of property crime increase on the downwind side of an interstate.

[31]As an illustration, consider the most inclusive possible rule, where the angle of inclusion was 90 degrees. In this case, if the average wind vector over the course of a day blows at all towards one side of the interstate, we consider that side treated on that particular day. Using I-290 once again as an example, if the wind fluctuated from due NW to due SW, but the average wind vector was 271 degrees, the most generous inclusion rule would classify the north side of the road as treated, despite pollution affecting both sides of the road.

[32]Examining outcomes, Anderson (2019) focuses on a narrow band around the interstate.

ment effect from a separate regression. The columns correspond to different angles necessary to qualify as "downwind," while the rows correspond to the size of the "collar" drawn around each interstate highway. For example, the top-left most cell reports the treatment effect estimated using crimes that happen within one-quarter mile of an interstate and only using days during which the average wind vector is within 36 degrees of the vector orthogonal to the direction of the highway (the most restrictive inclusion rule considered). Moving to the left in the table, we gradually relax the angle necessary for inclusion in the sample. Moving down, we extend the collar around the interstate to consider crimes within one-half mile distance and one mile distance, respectively. The estimate of the effect on the number of downwind crimes using sample inclusion restrictions from the main specification (that in column 4 from Table 4) is highlighted in bold.[33]

Although not dispositive, the results are broadly consistent with what we would expect if pollution were the driving mechanism. Extending the angle for inclusion increases the size of the estimation sample. While this improves the precision of the estimates (moving from left to right across the table, standard errors monotonically decline), increasing the angle for inclusion tends to attenuate the point estimate of the downwind effect, especially as we move towards the most generous values. This result is analogous to the attenuation of an intent-to-treat estimate caused by non-compliance. Moving down the rows of estimates, the size of the band on either side of the interstate varies between one-quarter mile and one mile. Although the area of the area of the study region doubles as we increase the bounds from one-quarter mile to one-half mile and then from one-half mile to one mile, the estimated treatment effect does not increase commensurately. This suggests that the downwind impacts are greatest near to the roadway and that the marginal effect on crime diminishes with distance to the interstate, consistent with the observational evidence in Karner, Eisinger and Niemeier (2010) .[34]

As a second test of pollution as the driving mechanism, we also examine the timing of treatment. Much of the literature examining the short-run impacts of pollution on health (e.g., Schlenker and Walker (2016)) and productivity (e.g., Zivin and Neidell (2012), Chang et al. (2019)) document the immediate (and short-lived) impacts of pollution exposure, noting that deleterious impacts arise from contemporaneous rather than lagged exposure. As a test, we regress crime on a particular day on comtemporaneous treatment as well as seven leads and

[33]The point estimate different from that in the main specification, since here we use the number of crimes as the dependent variable. Normalizing by the mean number of crimes, we obtain the point estimate from Table 4, panel A, column 4.

[34]As further check, in Appendix A.A2 we demonstrate that the downwind effect of pollution is strongest and most cleanly estimated on days during which the wind is blowing between 5-10 miles per hour. This is consistent with observational evidence from the wind-rose in figure 2, that suggests downwind pollution readings peak with wind-speeds of roughly 2-4 meters per second (5-10 mph). At these speeds, the wind is sufficient strong to ensure that the pollution is pushed to one side of the road. But, at higher speeds, pollution is dispersed more quickly.

lags of the treatment. We plot the coefficient estimates for past, contemporaneous and future treatment in Figure 4.[35] The coefficient estimates for lagged treatment are all indistinguishable from zero, consistent with the previous literature that suggests short-lived impacts of pollution exposure. In addition, the coefficients on future treatment status are also indistinguishable from zero, as would be expected by their placebo status.

Finally, if exposure to downwind exposure is the mechanism driving our observed effects, we might also expect the effect of downwind exposure to increase in seasons and days of the year where people are more likely to be outside and exposed to the pollution. In figure 5, we graph the coefficients and 95% confidence intervals for treatment effects that vary by season (left) and by daily maximum temperature bin (right).[36] On each plot, the dotted horizontal line corresponds to the treatment effect from our main specification, Table 4, panel A, column 4.

Although estimating separate coefficients for each season and temperature bin reduces the statistical power of our substantially, we find results generally consistent with downwind outdoor exposure as the mechanism. Across the four specifications, the effect of being downwind of the interstate has the largest impact during the spring and summer months. Relative to the 1.9 percent increase in violent crimes over the entire year, being the downwind side of the interstate is associated with a three to five percent increase in violent crime in the spring and summer. In contrast, the winter and fall treatment effects are not statistically after conditioning on fixed effects. In a similar vein, the relationship between temperature and the downwind treatment effect is generally concave and peaks on comfortable days with maximum daily temperatures between $20 - 24\,\text{deg}$ Celsius ($68 - 75\,\text{deg}$ Fahrenheit).

C. Placebo Interstate Test

The local nature of our identification strategy also allows for a placebo test of road pollution as the mechanism. To motivate the placebo test, consider the following thought exercise. Suppose we did not know *ex ante* the latitude at which I-290 cuts straight east/west through the city of Chicago. We could estimate downwind coefficients from our model at a number of different latitudes. We could then examine whether the effect on violent crime of being downwind was

[35]We also present a lagged version of our main specification in the appendix that includes leading and lagging values of the treatment variable (as well as lagged values of crime). As in figure 4, leading and lagging values of the downwind treatment are uncorrelated with violent crime, although consistent with Jacob, Lefgren and Moretti (2007) we find evidence that crime is serially correlated. Moreover, the coefficient on the contemporaneous value of the downwind treatment is virtually unchanged with the inclusion of lagged treatment variables, again consistent with the hypothesis that it is contemporaneous exposure as the driving mechanism.

[36]The specifications in green include interstate*date fixed effects and correspond to the specification in column 3 of 4. The specifications in red additionally include interstate*side fixed effects interacted with daily maximum temperature and total precipitation and correspond to the specification in column 4 of Table 4. For completeness, we report the full regression tables in Appendix tables A.4 and A.5, respectively.

greatest at the latitude of I-290. If we found large effects at alternative latitudes, we might worry that our downwind treatment was capturing effects other than pollution from mobile sources.

To conduct the exercise, we focus on crimes at similar longitudes to the crimes in our sample set for I-290, but extending far north and south of I-290. Figure 6 maps the latitude and longitudes of the crimes we use for the falsification test in green and the location of the interstates in red. Moving from the south to the north in one mile increments, we consider alternative latitudes. At each latitude, we conduct a t-test equivalent to the main specification in equation (3). We calculate the daily difference in violent crimes one mile north of the alternative latitude to that one mile south of the latitude. We then test whether the north-south violent crime differential at each latitude is greater on days when the wind blows to the north than when the wind blows to the south.

Figure 7 plots the difference in the north-south violent crime differential on days when the wind is blowing to north at each alternative latitude. The interpretation of the point estimate is identical to the interpretation of the downwind treatment in column 3 of Table 4, although in this case, the exercise only examines one of the seven interstate segments.[37] Three points in particular stand out. First, the maximum estimated downwind effect (in the center of the graph) is exactly at the latitude that I-290 cuts east-west through Chicago. Second, just to the right of the peak, corresponding to a latitude one mile north of I-290, we find the lowest estimated value for the downwind effect. This is exactly what we would expect if winds from the south blow pollution from the I-290 onto the *south side* of the placebo latitude one mile north of I-290.[38] The sharp rebound at latitudes just north of the minimum estimated downwind effect is also reassuring. This is consistent with the source of pollution being local to the latitude at which I-290 cuts through Chicago from east to west and dispersing at latitudes further north. Finally, the second highest peak on the graph (at a latitude 41.84 N) is roughly at the the latitude of I-55 as passes through the falsification test region.

D. Alternative identification strategy

As a final analysis, we consider an alternative identification strategy that exploits a different source of wind-induced variation. In the main specification, we included route-side and route-date fixed effects. Thus, our main estimates compare crime on the "treated" downwind side of the interstate to the upwind "control" region on the same day.

[37]We focus on I-290 for the falsification test as the city of Chicago extends further to the north and south, than to the east and west. Thus, we can create the greatest number of "placebo interstates" to I-290.

[38]This, incidently, provides evidence counter to the hypothesis that the impacts are driven by downwind noise propagation. The Chicago Transit Authority Green line is an elevated light rail line that runs parallel to I-290 roughly one mile north of I-290 and generates significant noise pollution (see e.g., `https://rosap.ntl.bts.gov/view/dot/10143/dot_10143_DS1.pdf`). If our downwind impacts reflect noise pollution, one might expect elevated levels of violent crime downwind of at this placebo latitude, rather than the diminished levels actually observed.

As an alternative, we exploit the length of our panel and compare crime within the same region on the same day of the year (e.g., the north-side of I-290 on July 4th) across across different years. That is, if a given side of an interstate is downwind for a higher fraction of hours on a particular day (say July 4th, 2011) than on the typical July 4th, we test whether we observe an increase in violent crime.

Relative to the identification strategy that uses the upwind side of an interstate as a control for crime on the downwind side, this approach directly addresses seasonal unobservables correlated with both criminal activity and prevailing wind patterns. For example, suppose that, for whatever reason, people flock to the north-side of I-290 on July 4th and, moreover, that side of the interstate tends to be downwind at that time of the year. Using the identification strategy that leverages opposite sides of the interstate, we might misattribute the uptick in crime arising from the July 4th uptick in activity to pollution. While, admittedly, this might be unlikely given the seven interstate segments we examine, the alternative identification strategy addresses this concern directly, by identifying the effect from variation in downwind exposure of the same location on the same day of the year.

Formally, for interstate i, side s, day-of-year d, and date t, we estimate

$$Crime_{ist} = \alpha_{isd} + \beta Downwind_{ist} + \Lambda X_{it} + \epsilon_{ist}. \tag{5}$$

where $Downwind_{ist}$ is a measure of how much downwind exposure interstate i, side s receives on a given date t and X_{it} includes weather covariates. We also include interstate-side-day-of-year fixed effects to capture the average level of violent crime on a side of an interstate on a particular day of the year (i.e., the north side of I-290 on July 4ths).

We construct two measures of daily downwind pollution exposure. First, we use the fraction of hours of a given day that the wind was blowing to that side of the road. In any given hour, we classify a side of the road as either treated or not treated if the wind is blowing towards the side at all, akin to the most generous inclusion rule for our main specification. We average the hourly values over the course of the day. This measure varies from 0 to 1, reflecting steady winds either away from or towards a particular side, respectively. As an alternative, we allow magnitude of the hourly treatment to vary based on the wind vector relative to the direction of the interstate. As suggested by figure 2, pollution readings just north of I-290 are greatest when the wind blows from the south. Pollution readings are slightly more modest when the wind blows parallel to the road. Intuitively, if the wind blows directly towards one side is a treats a side more strongly than if the wind is blowing at an angle to the vector of orthogonality. Thus, in each hour we calculate the cosine of the angle of the wind relative to the angle of orthogonality. This creates an continuous hourly variable equal to 1 if the wind is blowing directly towards one side of the interstate and -1 if the wind is blowing directly the side of the interstate which we average to create a daily measure.

Table 7 presents the results. In the first three columns, we present the results using the fraction of hours of the day the wind was blowing to that side of the road as our treatment variable. Using the fraction of downwind hours (in columns 1 through 3) as a measure of treatment intensity, we find a route-side has 2.4 percent more violent crimes on a day when it is downwind for every hour than a day when it is upwind for every hour. Refining the measure of downwind exposure in columns 4 through 6 doesn't fundamentally change our conclusions. As the treatment variable varies from -1 (i.e., completely downwind) to 1 (i.e., completely upwind), we estimate a 3.6 percent increase in violent crime. These magnitudes are very similar to those in our main specification, even though the exogenous variation in wind exposure is coming from a comparison with different implicit control group, namely the same side of the interstate on the same day of the year, but in years in which the segment was more or less "downwind".

V. Policy Implications

Our finding of a causal relationship between pollution and violent crime has two clear policy consequences. First, a Pigouvian tax or external cost estimate for local pollutants excluding the cost of crime would be understated. Second, our results contribute to the growing literature that suggests that pollution exposure might have adverse effect on cognition and behavior that extend more widely than previously considered.

Although we estimate that the effect of pollution on crime is modest in percentage terms, the annual aggregate costs of crime are enormous. Estimates from the literature vary in magnitude: more conservative estimates suggest crime imposes external costs of several hundred billion dollars per year annually in the U.S., while the upper end of estimates Anderson (1999) puts the aggregate cost of crime at over one trillion dollars annually.

Our paper provides two estimates of the crime costs generated by exposure to pollution. Focusing specifically on our estimates of downwind pollution exposure from interstates, we can compute a back-of-the-envelope estimate of the additional annual cost of crime from downwind exposure to major interstates. Although focused very specifically on a subset of urban neighborhoods close to interstates, this estimate speaks to a growing literature that studies variation in pollution exposure at the sub-metropolitan level. To do so, we apply cost of crime estimates from the literature and work under the conservative assumption that all additional violent crimes are assaults.[39] We also conduct the back of the envelope calculation under the assumption that pollution exposure doesn't shift the timing of criminal activity or the location of crimes. We find little evidence of intertemporal shifting (as the estimates of lagged effects of downwind

[39]Details of the calculation are in Appendix A.A3.

exposure are all close to and indistinguishable from zero), but the local nature of our identification strategy makes similar test of spatial shifting difficult. To the extent that crime shifts from the upwind to the downwind side of an interstate in response to wind direction, we would overestimate the true cost.[40] Scaling our estimates from Chicago up to the United States, we estimate annual costs of crime associated with downwind interstate pollution at $178 million per year. As a point of reference, these estimates are of roughly similar magnitude to the cost of traffic congestion on pre-term births ($444 million per year) estimated by Currie and Walker (2011).

A second benchmark broadens the scope to consider pollution more broadly, using the city-wide estimates from table 2. In the IV regressions, we estimate a one-standard deviation decrease in PM10 pollution is associated with a 2.9 percent reduction in violent crime. Between 2001 and 2012, average PM_{10} levels across all monitors in the Chicago metro area fell from roughly $28\mu g/m^3$ to $18\mu g/m^3$.[41] Relative to the variation used to estimate the city-level regressions, this reflects a 0.69 standard deviation decrease in average PM_{10} levels city-wide. Taken at face value, this would translate to a 2 percent reduction in violent crime using the IV estimates from table 2. Obviously, a shortcoming of this calculation (and a limitation of the city-wide estimates that we acknowledge) is that air pollution (across a wide range of pollutants) is declining over the study period and this back-of-the-envelope calculation treats PM_{10} emissions as a proxy for all pollutants. But, over the study period, 2001 to 2012, levels of PM_{10} and other pollutants declined by similar magnitudes. Average NOx, PM2.5 and PM_{10} readings in the Chicago area fell 35, 30 and 36 percent from 2001 to 2012. On base of roughly 46 thousand violent crimes in Chicago in 2001, a 2 percent reduction violent crimes would correspond to 920 less violent crimes.[42] Assuming these crimes were entirely the least costly violent crime (assaults), the crime reduction benefits for Chicago from pollution reduction over 2001 - 2012 might be conservatively estimated at $22 million per annum. Scaling up to the urban population of the U.S., the estimate would rise to $2.2 billion per annum.

We do not take a stand on the exact underlying mechanism, but our results suggest that air pollution may impact behavior in economically-meaningful ways much more broad than previously considered. Although we focus on violent criminal activity as an outcome, the potential underlying loss of control and in-

[40] In terms of a planner interested in aggregate crime the question of spatial displacement – criminal behavior being shifted from one neighborhood to another - is an important one. While our interstate analysis does not allow us to tackle this directly it is worth recalling that the city-level analysis supported the existence of a net effect of pollution. It is also the case that the interstates themselves offer a substantial barrier to mobility between neighborhoods adjacent but on alternative sides, potentially mitigating this concern given our approach to identification.

[41] A host of policies at the local, state and federal level contribute to this reduction. For mobile sources, the Chicago metro area began to require smog checks in the late 1990s, which combined with the gradual retirement of vehicles lacking catalytic converters, reduced pollution from mobile sources. Similar emissions reductions occurred from industrial point sources, with the introduction and increased stringency of the US Acid Rain program (targeting sulfur dioxide) and NoX budget program.

[42] As a point of comparison, rates of violent crime in Chicago fell by roughly 40 percent over this period.

creased impulsivity may be related to other economically important decisions. These results also provide insight into potential behavioral explanations behind lost productivity and performance found by previous studies. Finally, we see our results as complementary to the literature on the cognitive effects of poverty (see, e.g., Mani et al. (2013); Schilbach, Schofield and Mullainanathan (2016)), in which cognitive load and stress lead to poor decision-making. Pollution exposure may have similar effects, which adds an additional dimension of concern to policy debates about environmental justice, disproportional pollution burdens amongst demographic groups within the United States and high levels of pollution in the developing world.

VI. Conclusion

The primary contribution of this paper is to identify a causal link from short-run variation in air pollution to violent crime. Our approach exploits variation in air quality induced by naturally occurring changes in wind direction in the city of Chicago. At the aggregate city-level, we exploit wind-driven pollution shocks from industrial facilities to the southeast and southwest of the metro area and estimate that a one-standard deviation decrease in PM_{10} pollution is associated with a 2.9 percent reduction in violent crime.

We complement the city-wide evidence with evidence that exploits the micro-geography of pollution and crime within Chicago. We study days during which the wind blows orthogonally to a major interstate such as the I-290 and use the upwind side of the interstate as a control for the treated downwind side. We find estimates broadly similar to the aggregate data (and to more recent papers studying pollution and crime). As in the city-level evidence, we find an increase in violent crime (but not property crime) on the downwind side of the interstate. Consistent with literature from medicine and psychology of a short-term impact of pollution on aggression, we find that contemporaneous is most relevant, rather than lagged exposure. Furthermore, we find that as we alter the rules for constructing the study sample, the estimated magnitude of the treatment effect changes as we would expect if air pollution were the driving mechanism.

In Chicago violent crime increases by 1.9% in a neighborhood on the downwind side of a major interstate. Back of the envelope calculations based on these magnitudes suggest that the cost to society is meaningful compared to other outcomes studied in the external costs literature.

Our work contributes to the growing recognition that, in addition to the well-understood health benefits, air pollution may impact behavior and cognition in broader ways than previously considered. From a policy standpoint, the analysis suggests additional social cost of air pollution and that estimates of the marginal social cost may be greater that previously considered.

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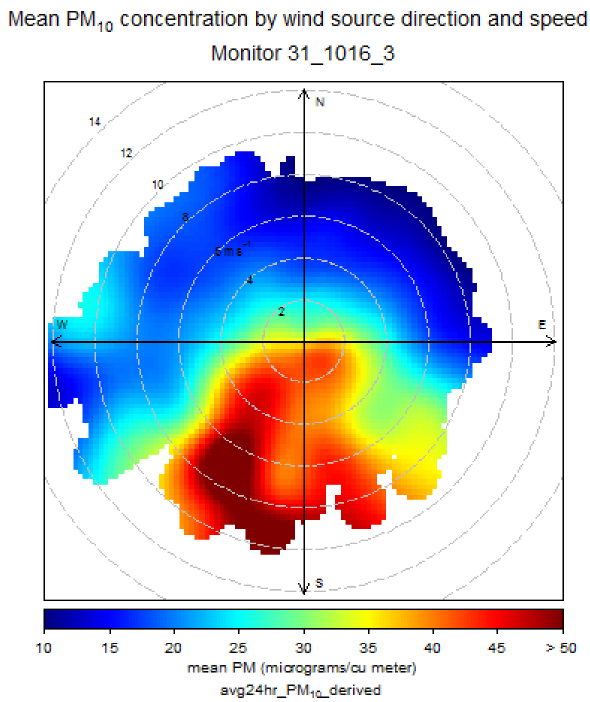
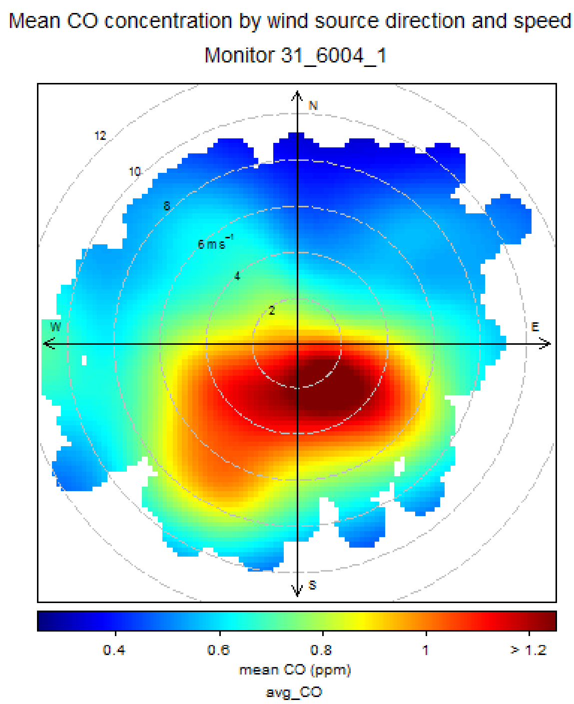
VII. Tables and Figures

Figure 1. : Average PM_{10} reading
by wind direction and vector-based speed



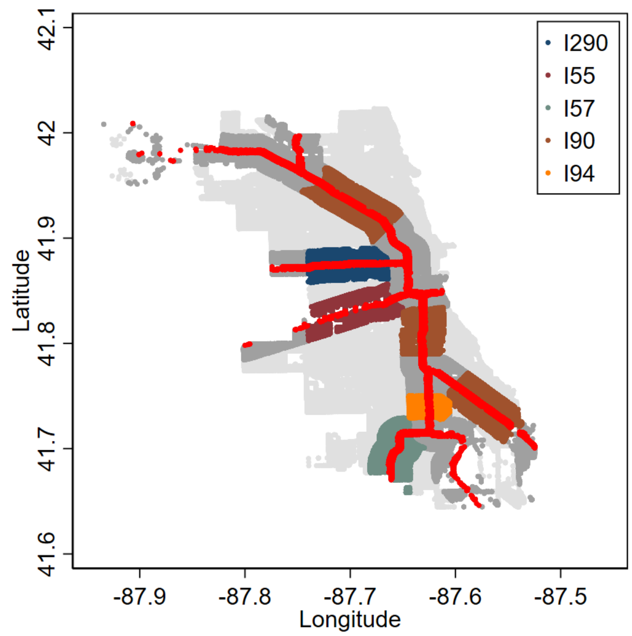
Note: Shading denotes mean hourly PM_{10} readings over sample period at Monitor 31-1016-3. The vector from the origin to a particular point denotes the direction from which wind is blowing and the distance from the origin denotes average wind speed (in meters/second). For example, the point (0, 2) reflects average emissions in an hour during which the wind is blowing from the East at 2 meters per second.

Figure 2. : Average CO reading near I-290
by wind direction and vector-based speed



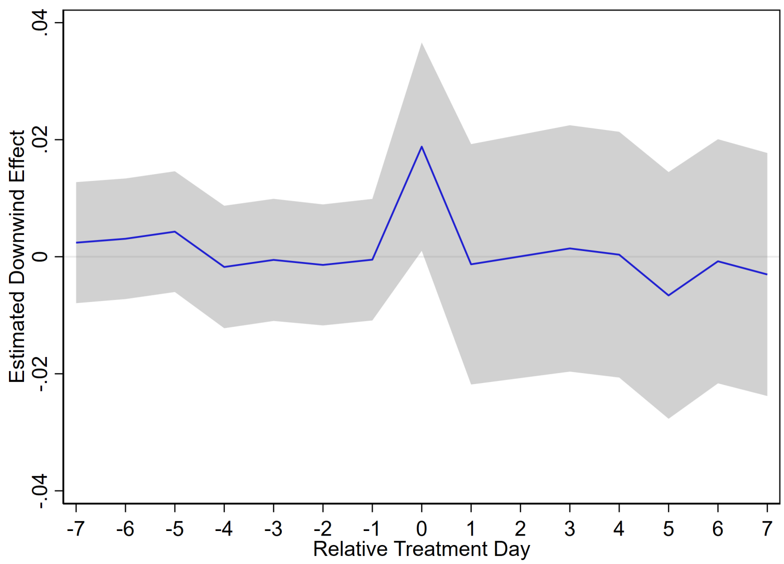
Note: Shading denotes denote mean hourly PM_{10} readings over sample period at Monitor 31-6004-1. The vector from the origin to a particular point denotes the direction from which wind is blowing and the distance from the origin denotes average wind speed (in meters/second). For example, the point (0, 2) reflects average emissions in an hour during which the wind is blowing from the East at 2 meters per second.

Figure 3. : Sample set for interstate identification strategy



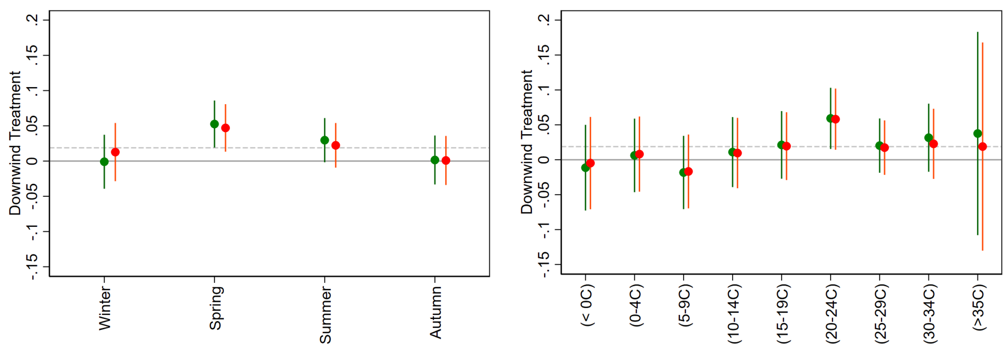
Note: Figure plots the latitude and longitude of all crimes in light grey, crimes within one mile of an interstate in Chicago in dark grey, the location of the interstates in red, and the seven interstate segments used for the interstate analysis in color.

Figure 4. : Leading and Lagging Downwind Treatment Effects



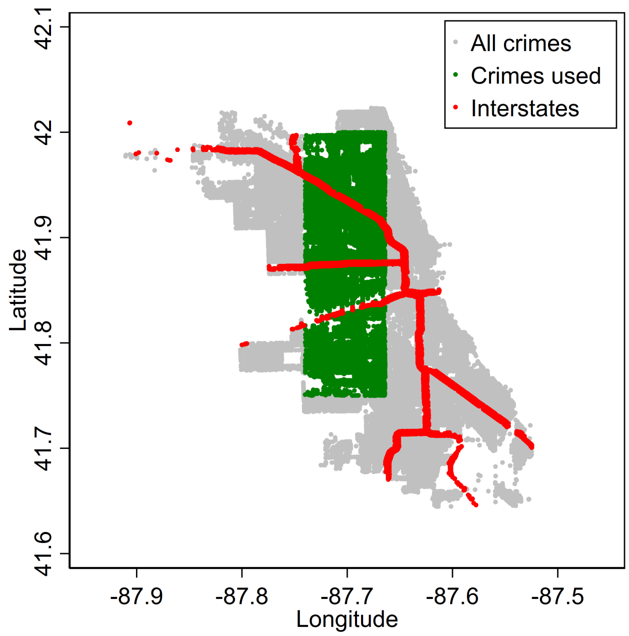
Note: Figure plots the coefficient estimates and 95 percent confidence interval of lagged and leading downwind treatment dummies. The dependent variable is the number of crimes within one mile of one side of the interstate normalized by the mean number of crimes. All specifications include interstate*date fixed effects and interstate*side fixed effects interacted with daily maximum temperature and total precipitation.

Figure 5. : Downwind coefficients, by Season and Temperature



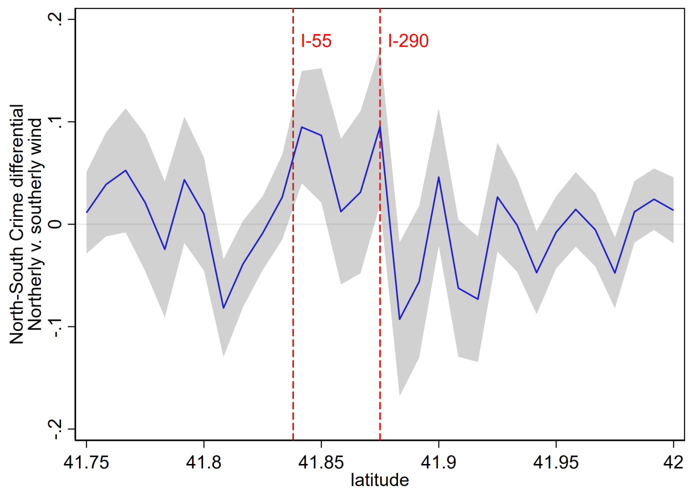
Note: Figure plots the coefficient estimates and 95 percent confidence intervals for interactions between the downwind treatment and season of the year (left) and daily temperature bins (right). The dependent variable is the number of crimes within one mile of one side of the interstate normalized by the mean number of crimes. The specifications in green include interstate*date fixed effects and correspond to the specification in column 3 of 4. The specifications in red additionally include interstate*side fixed effects interacted with daily maximum temperature and total precipitation and correspond to the specification in column 4 of Table 4. The dotted horizontal line denotes the point estimate of the downwind treatment (0.188) from Table 4. For completeness, the underlying regression results are reported in the Appendix.

Figure 6. : Sample set for falsification test



Note: Figure plots the latitude and longitude of all crimes in Chicago in grey, the sample set of crimes used for the analysis of the placebo interstates in green, and the location of the interstates in red.

Figure 7. : North-south crime differential, alternative latitudes



Note: The y-axis reports the difference in the number of violent crimes one mile north versus one mile south of the latitude reported on days when the wind is blowing northernly rather than southernly. Northernly and southernly are defined as within 60 degrees of north and south, respectively. The solid line denotes the point estimate of the difference and the dashed lines denote the upper and lower bounds of the 95% confidence interval of the t-test. The vertical lines denote the latitudes of I-290 and the average latitude of I-55.

Table 1—: Summary Statistics

	Mean	Std. Dev.
Citywide sample:		
Number of dates	3642	
Daily city-wide violent crime	57.4	18.7
Daily city-wide property crime	420.1	68.4
Precipitation (mm)	2.75	7.74
Maximum temperature (°C)	15.5	11.6
Daily avg. carbon monoxide (ppm)	0.59	0.27
Daily avg. NO2 (ppm)	0.027	0.0084
Daily avg. ozone (ppm)	0.023	0.012
Daily avg. PM10 ($\mu g/m^3$)	27.7	14.4
Wind speed (km/h)	12.3	4.40
Dew point (°C)	4.44	10.1
Air pressure (hpa)	1016.6	7.09
Cloud cover sunrise to sunset (percent)	63.8	27.7
Interstate sample:		
Interstate-side-days	41730	
Daily interstate-side violent crimes	1.1	1.4
Daily interstate-side property crimes	7.3	5.2

Table 2—: PM_{10} impact on daily part 1 crime, 2001-2012

	Violent Crimes			Property Crimes		
	(1) OLS	(2) OLS	(3) IV	(4) OLS	(5) OLS	(6) IV
Standardized PM10 Reading	0.061***	0.014***	0.029**	0.0041***	-0.0013	0.0013
	(0.0037)	(0.0043)	(0.013)	(0.0014)	(0.0019)	(0.0058)
First-stage F			26.4			26.4
Calendar FE	X	X	X	X	X	X
Weather Controls		X	X		X	X
Historical Mean Temp		X	X		X	X
Observations	3642	3642	3642	3642	3642	3642
R-Squared	0.69	0.75	0.75	0.79	0.81	0.81

Notes: *** p<0.01, ** p<0.05, * p<0.1. Newey-West robust standard errors reported. Dependent variable is the log of the daily number of violent crimes (columns 1 - 3) and log of the daily number of property crimes (columns 4 - 6). Calendar fixed effects include year-month fixed effects, day of week fixed effects, and first-of-month, first-of-year and holiday dummies. Weather variables in include binned maximum daily temperature, binned dew point, precipitation, barometric pressure and average sky cover. Historical mean temperature is the average maximum temperature over 1991 - 2000 matched by day-of-year to the study period. Excluded instruments are 20 degree bins for daily average wind direction at Midway Airport. The pollution variable of interest is the standardized mean reading over monitors 31-22-3 and 31-1016-3.

Table 3—: PM_{10} impact on daily part 1 and non-part1 crime, 2001-2012

	Violent			Non-Violent		
	(1) FBI Part 1	(2) Not Part 1	(3) All	(4) FBI Part 1	(5) Not Part 1	(6) All
Standardized PM10 Reading	0.029**	0.014*	0.017**	0.0013	0.0091	0.0055
	(0.013)	(0.0080)	(0.0076)	(0.0058)	(0.0070)	(0.0053)
Calendar FE	X	X	X	X	X	X
Weather Controls	X	X	X	X	X	X
Historical Mean Temp	X	X	X	X	X	X
Observations	3642	3642	3642	3642	3642	3642
R-Squared	0.75	0.77	0.81	0.81	0.72	0.80

Notes: *** p<0.01, ** p<0.05, * p<0.1. Newey-West robust standard errors reported. Dependent variable is the log of the daily number Part 1 violent and non-violent crimes (columns 1 and 4), non-Part 1 violent and non-violent crimes (columns 2 and 5) and all violent and non-violent crimes (columns 3 and 6). Calendar fixed effects include year-month fixed effects, day of week fixed effects, and first-of-month, first-of-year and holiday dummies. Weather variables in include binned maximum daily temperature, binned dew point, precipitation, barometric pressure and average sky cover. Historical mean temperature is the average maximum temperature over 1991 - 2000 matched by day-of-year to the study period. All specifications instrument for pollution using 20 degree bins for daily average wind direction at Midway Airport. The pollution variable of interest is the standardized mean reading over monitors 31-22-3 and 31-1016-3.

Table 4—: Crime downwind of interstates

Panel A: Violent Crime

	(1)	(2)	(3)	(4)
Treatment (downwind)	0.0558***	0.0186**	0.0186**	0.0188**
	(0.0108)	(0.0094)	(0.0089)	(0.0091)
Route-Side FE		X	X	X
Route-Date FE			X	X
Route-Side Weather Interact				X
Observations	41730	41730	41730	41720
R-Squared	0.001	0.274	0.678	0.680

Panel B: Property Crime

	(1)	(2)	(3)	(4)
Treatment (downwind)	0.0015	-0.0014	-0.0014	-0.0007
	(0.0071)	(0.0046)	(0.0041)	(0.0043)
Route*Side FE		X	X	X
Route*Date FE			X	X
Route*Side Weather Interact.				X
Observations	41730	41730	41730	41720
R-Squared	0.000	0.609	0.841	0.843

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate normalized by the mean number of crimes. A side of the interstate is considered downwind if the average wind vector over the course of the day is within 60 degrees of the vector orthogonal to the direction of the interstate.

Table 5—: Violent crime downwind of interstates, by specific crime

	(1) Homocide	(2) Rape	(3) Agg. Assault	(4) Agg. Battery
Treatment (downwind)	0.00228	0.00310	-0.0119*	0.0299***
	(0.00185)	(0.00293)	(0.00610)	(0.00862)
Dep. Var. Mean	0.029	0.083	0.338	0.638
Route*Side FE	X	X	X	X
Route*Date FE	X	X	X	X
Route*Side Weather. Interact.	X	X	X	X
Observations	41720	41720	41720	41720
R-Squared	0.510	0.529	0.563	0.651

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate. A side of the interstate is considered downwind if the average wind vector over the course of the day is within 60 degrees of the vector orthogonal to the direction of the interstate. All specifications include interstate*date fixed effects and interstate*side fixed effects interacted with daily maximum temperature and total precipitation.

Table 6—: Violent crime downwind of interstates, by treatment angle and distance from interstate

	Angle width	36	45	60	75	90
$\frac{1}{4}$ mile						
	Est.	0.0075	0.0112*	0.0137***	0.0100**	0.0090**
	SE	(0.0069)	(0.0060)	(0.0051)	(0.0044)	(0.0040)
	N	24760	31250	41730	51924	61362
	R^2	0.579	0.582	0.588	0.587	0.588
$\frac{1}{2}$ mile						
	Est.	0.0145	0.0168*	0.0160**	0.0154**	0.0164***
	SE	(0.0105)	(0.0092)	(0.0077)	(0.0067)	(0.0061)
	N	24760	31250	41730	51924	61362
	R^2	0.637	0.639	0.642	0.641	0.64
1 mile						
	Est.	0.0247	0.0235*	**0.0234****	0.0166*	0.0152*
	SE	(0.0153)	(0.0134)	**(0.0113)**	(0.0099)	(0.0090)
	N	24760	31250	**41730**	51924	61362
	R^2	0.676	0.678	**0.68**	0.68	0.679

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of an interstate. All specifications include interstate*date fixed effects and interstate*side fixed effects interacted with daily maximum temperature and total precipitation. The estimate using assumptions equivalent to those in Table 4, Panel A, column 4, is emboldened. For reference, the mean number of violent crimes at the interstate-side-day level is 0.225 within a quarter mile, 0.486 within a half-mile and 1.061 within a full mile.

Table 7—: Violent crime downwind of interstates, alternative specification

	Fraction of Hours			Average Cosine of Wind Vector		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (downwind)	0.0225**	0.0238**	0.0239**	0.0182***	0.0180**	0.0180**
	(0.00942)	(0.0103)	(0.0101)	(0.00676)	(0.00739)	(0.00717)
Route*Side*Month FE	X			X		
Route*Side*DoY FE		X	X		X	X
Covariate Interactions			X			X
Observations	61362	61362	61348	61362	61362	61348
R-Squared	0.301	0.356	0.369	0.301	0.356	0.369

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate normalized by the mean number of crimes. Columns 1 through 3 calculate daily downwind exposure as the fraction of hours a neighborhood is downwind of an interstate on a particular day. Columns 4 through 6 calculation daily downwind exposure as the mean cosine of the angular difference of the hourly wind vector relative and the vector orthogonal to the direction of the interstate segment (which varies from 1 to -1 forcompletely upwind and downwind days).

Appendix

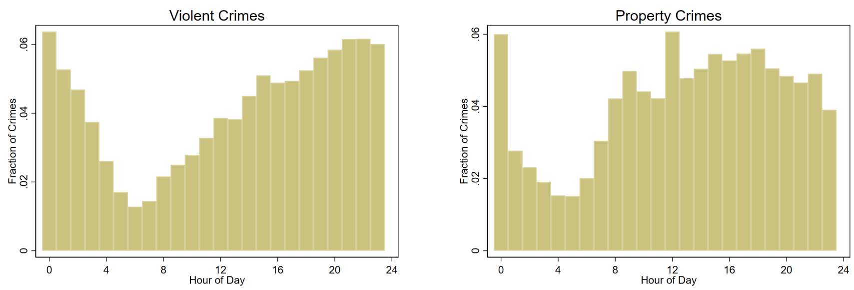
A1. Patterns of Crime in Chicago

Crime reports display certain temporal and seasonal regularities. As is clear from Figure A.1, reports of violent crime are lowest in the very early morning and steadily increase until midnight. Property crime reports also are lowest in the early morning, but tend to be higher during the day than at night. In Figure A.2, we present the average number of crimes for a given week of the year to consider seasonality. Two things are worth noting here. First, the absolute magnitude of property crime is roughly 6-7 times larger than that of violent crime. Second, the seasonal patterns are slightly different. While violent crimes are approximately symmetrical around their peak in the summer, property crimes tail off more slowly in the fall than they rise in the spring. Finally, Figure A.3 presents the annual trends in property and violent crimes between 2001 and 2012. Each type of crime's 2001 level is normalized to 100. Overall, violent crime has declined more rapidly than property crime, although both varieties are far below their 2001 levels.

In Figures A.1 and A.2, there are spikes in crime reports at midnight and in the first week of the year. If one looks at the day of the month, there is also a spike on the first of the month. Some of this is driven by the fact that the time and date in our data refer to the actual occurrence of the crime, not the report. Thus, if someone waits to report a crime or forgets the time and date exactly, they might be more likely to simply choose midnight or the first of the month. Correspondence with the Chicago Police Department's Research and Development Division indicates that there is no official procedure that would otherwise be driving this phenomenon. This effect is the largest for January 1, some of which could be driven by the New Year's Eve holiday. At any rate, we control for the 1st day of the month and year when appropriate in our citywide regressions. In our analyses using detailed geographic coordinates, we are comparing treatment and control areas within the same day, so any effect should be swept out.

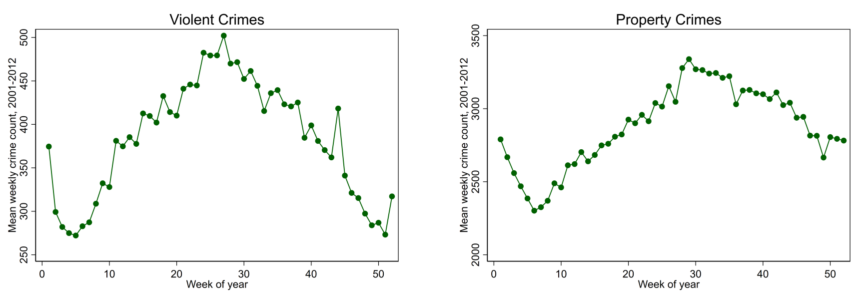
The geographic patterns of property versus violent crime also differ from one another. The heat maps in Figure A.4 plot the density of property and violent crime throughout Chicago for 2001-2012. The grey lines denote the major interstates running through the city limits. The shades are comparable only within a map; that is, an area on the violent crime map that is darker than an area on the property crime map does not necessarily indicate that there are more violent crimes in absolute terms. It simply means that the *share* of violent crimes that occur in that area is greater than the share of property crimes. The poorer areas, such as the South Side, and the westernmost portions of the West Side have experienced the most violent crime. Although these areas also experience high rates of property crime, the densest area for property crime is the Loop. Part of this may be driven by a higher population density overall, and part might be driven by high levels of economic activity.

Figure A.1. : Fraction of crimes by hour of day



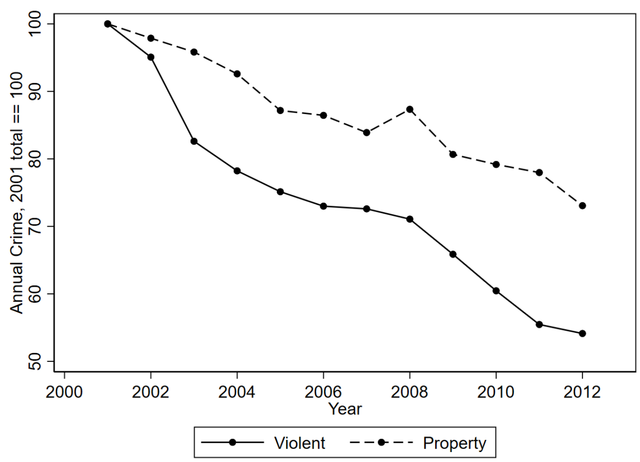
Note: Figure plots the fraction of part 1 violent crimes and property crimes reported by hour of day during the sample period.

Figure A.2. : Crimes by week of year



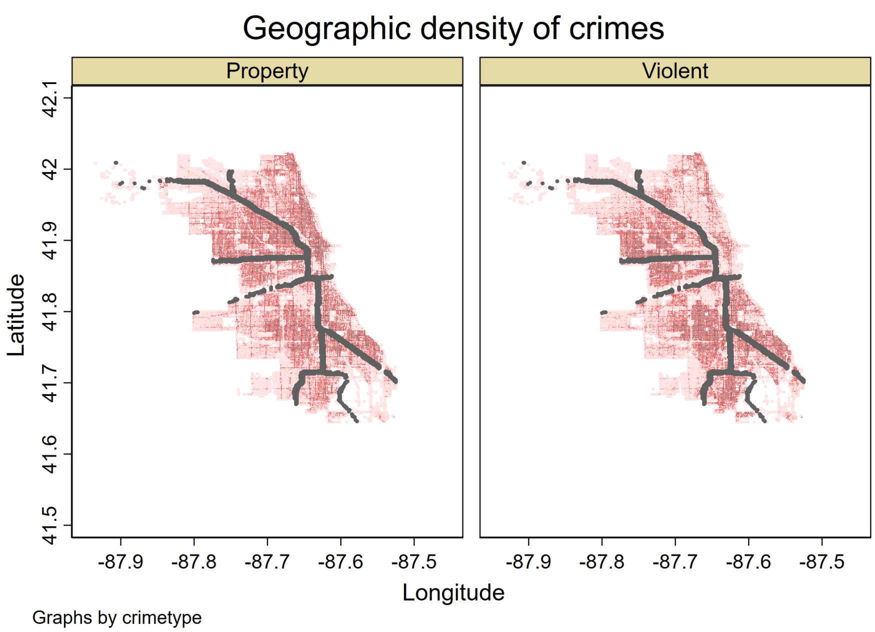
Note: Figure plots the mean number of part 1 violent crimes and property crimes reported by week-of-year during the sample period.

Figure A.3. : Normalized average annual crimes



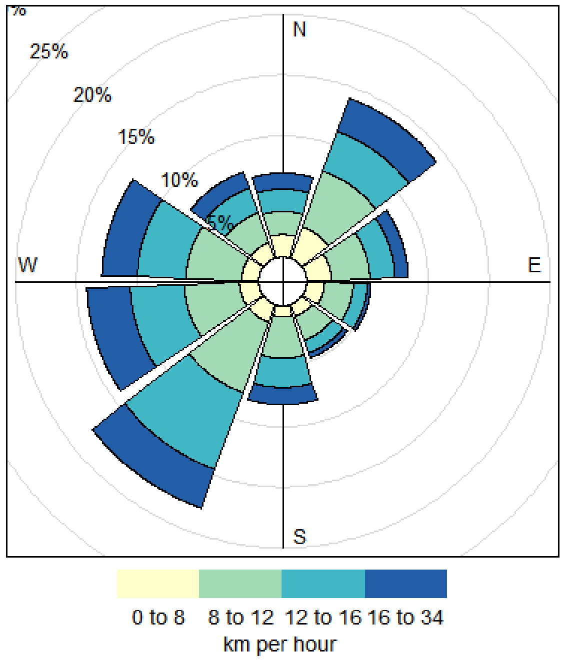
Note: Figure plots the annual number of part 1 violent and property crimes, normalized to 2001 levels (2001 levels = 100), during the sample period.

Figure A.4. : Crimes density heat maps



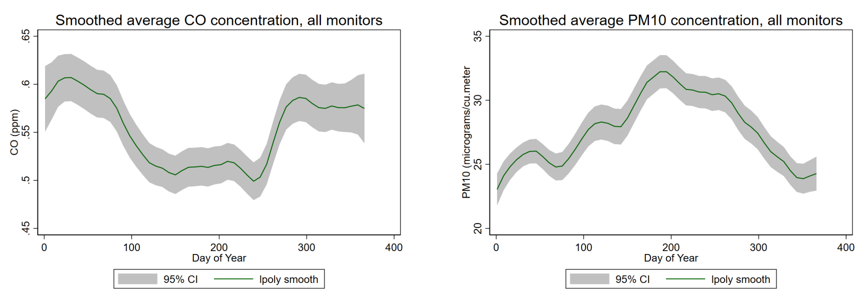
Note: Figure plots the density of part 1 property and violent crimes in Chicago during the sample period. Darker regions represent locations with more crimes. Grey lines correpond to the major interstates transecting the city.

Figure A.5. : Distribution of wind direction and speed



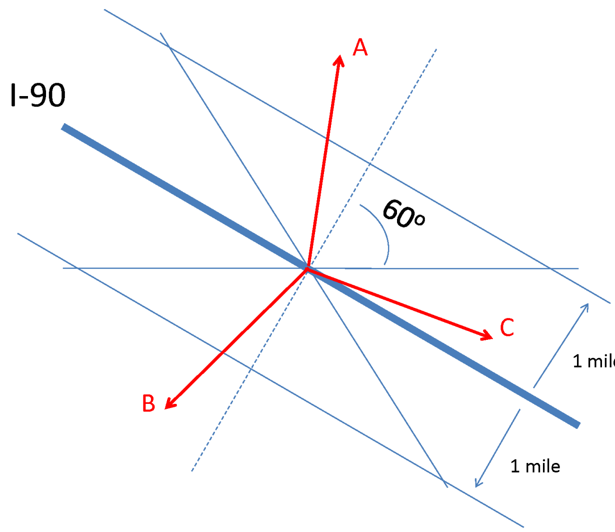
Note: Figure plots the "wind rose" histogram for Chicago during the sample period. The angle from the origin represents the vector from which the wind is blowing (in 36 degree increment bins). Shading represents the wind speed.

Figure A.6. : Seasonality in CO and PM10 emissions



Note: Figures present average CO and PM10 emissions readings (and 95% confidence intervals) from Chicago monitors, smoothed over the course of the year.

Figure A.7. : Upwind and Downwind Classification



Note: As an example, if the average wind direction over the course of a day was given by the vector A, the northeast side of I-90 would be classified as the treated downwind location. If wind direction were given by vector B, the southwest side would be classified as downwind. And if wind direction were given by vector C, the neither side would be considered downwind, as vector C is not within sixty degrees of the line of orthogonality.

A2. Supplementary evidence

Table A.1—: Downwind violent crime, alternative dependent variables

	Number of Crimes			Percent of Mean			Poisson Regression		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (downwind)	0.0694***	0.0231**	0.0234**	0.0558***	0.0186**	0.0188**	0.0638***	0.0210**	0.0199*
	(0.0134)	(0.0110)	(0.0113)	(0.0108)	(0.00887)	(0.00908)	(0.0123)	(0.0107)	(0.0106)
Route-Side FE		X	X		X	X	X	X	X
Route-Date FE		X	X		X	X	X	X	X
Route-Side Weather Interact			X			X			X
Observations	41730	41730	41720	41730	41730	41720	41730	41730	41720
R-Squared	0.000644	0.678	0.680	0.000644	0.678	0.680			

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors reported. In specifications 1 through 3, the dependent variable is the number of violent FBI Part 1 crimes within one mile of one side of the interstate on a given day. In specifications 4 through 6, we normalize the number of violent FBI part 1 crimes by the mean number of crimes over the sample. Columns 7 through 9 estimate Poisson models of the number of violent FBI Part 1 crimes. Columns 1, 4 and 7 do not include covariates. Columns 2, 5 and 8 include interstate-side fixed effects and interstate-date fixed effects. Columns 3, 6 and 9 further include interstate-side interactions with continuous weather covariates. Treatment is defined at the interstate-side-day level. An interstate-side is treated on a given day if, over the course of the day, the average wind vector is within sixty degrees of the vector orthogonal to the direction of the interstate.

Table A.2—: Downwind Violent Crime, Alternative Standard Errors

	(1)	(2)	(3)	(4)
Treatment (downwind)	0.0558***	0.0186**	0.0186**	0.0188**
	(0.00925)	(0.00887)	(0.00887)	(0.00908)
P-values:				
Robust	0	0.0370	0.0370	0.0380
Newey West	0	0.0370	0.0370	0.0390
Clustered Route-Month-Year	0	0.0450	0.0450	0.0410
WBC: Route-Month-Year	0	0.0320	0.0320	0.0320
Clustered Route-Year	0.00400	0.0420	0.0420	0.0530
WBC: Route-Year	0.00200	0.0410	0.0410	0.0550
Observations	41730	41730	41730	41720
R-Squared	0.630	0.678	0.678	0.680

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dependent variable is the number of violent FBI Part 1 crimes within one mile of one side of the interstate on a given day, normalized by the mean number of crimes. Columns 1 through 4 correspond to the specifications in our main table, allowing the downwind treatment variable to vary by day of the week. Treatment is defined at the interstate-side-day level. An interstate-side is treated on a given day if, over the course of the day, the average wind vector is within sixty degrees of the vector orthogonal to the direction of the interstate.

Table A.3—: Downwind violent crime, including lagged variables

	(1)	(2)	(3)	(4)	(5)
Treatment (downwind)	0.0188**	0.0239**	0.0234**	0.0240**	0.0242**
	(0.00908)	(0.0105)	(0.0105)	(0.0105)	(0.0106)
Number of crimes, t-1				0.0326***	0.0327***
				(0.00680)	(0.00680)
Treatment, t-1		-0.00402	-0.00223	-0.00296	-0.00281
		(0.00580)	(0.00609)	(0.00609)	(0.00609)
Treatment, t-2			-0.00586	-0.00559	-0.00607
			(0.00592)	(0.00592)	(0.00594)
Treatment, t-3			0.00123	0.00133	0.00353
			(0.00570)	(0.00570)	(0.00602)
Treatment, t-4					-0.00714
					(0.00607)
Treatment, t-5					0.00358
					(0.00600)
Treatment, t-6					0.000302
					(0.00602)
Treatment, t-7					0.000355
					(0.00571)
Treatment, t+1		-0.00418	-0.00488	-0.00474	-0.00470
		(0.00584)	(0.00615)	(0.00615)	(0.00616)
Treatment, t+2			0.00189	0.00163	0.00202
			(0.00604)	(0.00604)	(0.00606)
Treatment, t+3			0.00219	0.00210	0.000752
			(0.00581)	(0.00581)	(0.00614)
Treatment, t+4					0.00502
					(0.00607)
Treatment, t+5					-0.00237
					(0.00606)
Treatment, t+6					-0.00119
					(0.00609)
Treatment, t+7					-0.00272
					(0.00576)
Sum of Current					
and Lagged Effects		0.0199	0.0166	0.0168	0.0159
Standard Error		(.0102)	(.0119)	(.0119)	(.0141)
Observations	41720	41720	41720	41720	41720
R-Squared	0.680	0.680	0.680	0.681	0.681

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate normalized by the mean number of crimes. All specifications include interstate*date fixed effects and interstate*side fixed effects interacted with daily maximum temperature and total precipitation.

Table A.4—: Violent crime downwind of interstates, by season

	(1)	(2)	(3)	(4)
Treatment*Winter	0.0989***	-0.0010	-0.0010	0.0127
	(0.0226)	(0.0205)	(0.0195)	(0.0211)
Treatment*Spring	0.0333	0.0525***	0.0525***	0.0470***
	(0.0210)	(0.0178)	(0.0170)	(0.0172)
Treatment*Summer	0.0474**	0.0296*	0.0296*	0.0223
	(0.0201)	(0.0167)	(0.0160)	(0.0161)
Treatment*Autumn	0.0566***	0.0015	0.0015	0.0008
	(0.0216)	(0.0187)	(0.0177)	(0.0178)
Route*Side FE		X	X	X
Route*Date FE			X	X
Route*Side Weather Interact.				X
Observations	41730	41730	41730	41720
R-Squared	0.002	0.273	0.669	0.669

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate, normalized by the mean number of crimes in the season.

EFFECTS BY SEASON, TEMPERATURE BINS AND WIND SPEED BINS. —

Table A.5—: Violent crime downwind of interstates, by maximum daily temperature

	(1)	(2)	(3)	(4)
Treatment*(¡ 0C)	0.0915***	-0.0113	-0.0113	-0.0048
	(0.0353)	(0.0324)	(0.0313)	(0.0337)
Treatment*(0-4C)	0.0569*	0.0062	0.0062	0.0081
	(0.0315)	(0.0279)	(0.0269)	(0.0275)
Treatment*(5-9C)	0.0187	-0.0182	-0.0182	-0.0167
	(0.0317)	(0.0275)	(0.0268)	(0.0270)
Treatment*(10-14C)	0.0270	0.0110	0.0110	0.0096
	(0.0310)	(0.0265)	(0.0256)	(0.0257)
Treatment*(15-19C)	0.0295	0.0213	0.0213	0.0195
	(0.0304)	(0.0261)	(0.0247)	(0.0248)
Treatment*(20-24C)	0.0447	0.0593**	0.0593***	0.0581***
	(0.0279)	(0.0231)	(0.0223)	(0.0224)
Treatment*(25-29C)	0.0318	0.0203	0.0203	0.0174
	(0.0246)	(0.0205)	(0.0198)	(0.0199)
Treatment*(30-34C)	0.1434***	0.0316	0.0316	0.0228
	(0.0315)	(0.0264)	(0.0249)	(0.0256)
Treatment*(¿35C)	0.2390***	0.0376	0.0376	0.0189
	(0.0916)	(0.0766)	(0.0743)	(0.0760)
Route*Side FE		X	X	X
Route*Date FE			X	X
Route*Side Weather Interact.				X
Observations	41730	41730	41730	41720
R-Squared	0.003	0.272	0.662	0.663

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate, normalized by the mean number of crimes in the temperature bin.

As is clear from Figure 2, pollution on one side of a major interstate is correlated with both wind direction and wind speed. In particular, on calm days, we see pollution rises regardless of the direction of the breeze. This is due to the fact that without sufficient wind, pollution will 'pool' along both sides of the interstate. In addition, if the wind is sufficiently strong, the wind may disperse pollution sufficiently so as not to have a meaningful impact on exposure immediately downwind of the highway.

In Table A.6, we estimate separate downwind coefficients by wind-bin. In this way, we compare the effect of being downwind on a calm day, a day with a light wind that pushes but does not meaningfully disperse pollution, and days with strong winds that spread pollution from a highway beyond the area immediate proximate to the road. We find patterns roughly in line with the air transport predictions above. Winds between 2-4 meters per second (5 - 10 miles per hour) are associated with the largest, statistically precise impact of being downwind. Although strong winds are associated with larger point estimates, the point estimates are very imprecisely estimated due to the small fraction of days during which wind speeds average more than 20 miles per hour over the course of the day.

Table A.6—: Downwind violent crime, by wind bins

	(1)	(2)	(3)	(4)
Treatment*(Wind speed 0 - 2 m/s)	-0.1019*	-0.0033	-0.0033	0.0067
	(0.0558)	(0.0486)	(0.0475)	(0.0475)
Treatment*(Wind speed 2 - 4 m/s)	0.0379**	0.0258*	0.0258*	0.0271**
	(0.0167)	(0.0142)	(0.0134)	(0.0134)
Treatment*(Wind speed 4 - 6 m/s)	0.0776***	0.0120	0.0120	0.0110
	(0.0169)	(0.0148)	(0.0139)	(0.0141)
Treatment*(Wind speed 6 - 8 m/s)	0.0731**	0.0171	0.0171	0.0158
	(0.0315)	(0.0274)	(0.0257)	(0.0259)
Treatment*(Wind speed 8 - 10 m/s)	0.1197*	0.0564	0.0564	0.0528
	(0.0677)	(0.0584)	(0.0580)	(0.0580)
Treatment*(Wind speed 10 - 12 m/s)	0.3036	0.1630	0.1630	0.1542
	(0.2475)	(0.2177)	(0.1787)	(0.1776)
Route*Side FE		X	X	X
Route*Date FE			X	X
Route*Side Weather Interact.				X
Observations	41730	41730	41730	41720
R-Squared	0.001	0.274	0.677	0.679

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate.

PROPERTY CRIME SUBCATEGORIES. — Breaking down the property crime (Table A.7) results confirms that there is no effect within any particular type of crime that is being obscured by an opposite response among another type.

Table A.7—: Property crime downwind of interstates, by specific crime

	(1) Robbery	(2) Burglary	(3) Larceny	(4) Gr. Theft Auto	(5) Arson
Treatment (downwind)	0.00488	-0.00368	-0.00814	0.00291	-0.000777
	(0.0100)	(0.0125)	(0.0221)	(0.0115)	(0.00191)
Dep. Var. Mean	0.866	1.269	4.014	1.122	0.033
Route*Side FE	X	X	X	X	X
Route*Date FE	X	X	X	X	X
Route*Side Weather Interact.	X	X	X	X	X
Observations	41720	41720	41720	41720	41720
R-Squared	0.632	0.661	0.794	0.619	0.507

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors reported. The dependent variable is the number of crimes within one mile of one side of the interstate. A side of the interstate is considered downwind if the average wind vector over the course of the day is within 60 degrees of the vector orthogonal to the direction of the interstate.

A3. Cost of Crime Calculation based on Chicago Estimates

McCollister, French and Fang (2010) compute the comprehensive cost of each class of index crime. We use only the tangible costs of crime, which include medical expenses, cash losses, property theft or damage, and lost earnings because of injury, other victimization-related consequences, criminal justice costs, and career crime costs. We update their estimates to 2014 USD using the CPI. For the cost of homicide, we add the estimated judicial costs to the EPA's value of statistical life.[43]

In constructing our sample, we omit 48% of the crimes that occur within one mile of an interstate.[44] However, in calculating the total cost of pollution, we want to include these areas.[45] If we assume that each of the classes of violent crimes increase differentially according to the estimates from Table 5, the total annual cost of pollution-induced crime for the 14 interstate-sides amounts to $81.1 million. However, this figure is driven by the enormous cost of an additional homicide. If we assume that all additional violent crimes are, in fact, assault/batteries, the annual estimate falls to $1.8 million. The true value is likely somewhere between these two bounds as we omit intangible costs, do not account for the increased costliness of batteries over assaults, and do not consider the possible impact on non-index (more minor) crimes.

It is difficult to extrapolate this result to a nationwide calculation, given the diversity of urban form and density across the nation. To get a sense of the likely magnitude of nationwide costs, we assume that the pollution impacts of traffic scale up proportionally with population. The city of Chicago had a 2010 population of 2.7 million, while the total urban population of the United States in 2010 was 249.3 million (United States Census Bureau, 2010). As a lower bound, if we assume all additional violent crimes are assaults, the annual cost to the United States amounts to $178 million per year.

[43]In 2014 USD, the respective costs of a homicide, a rape, and an assault are $10.3 million; $51,165; and $24,234. The authors also compute intangible costs, such as pain and suffering. However, as Ranson (2014) notes, these are based largely on jury awards and may not accurately reflect willingness-to-pay to avoid victimization; thus, we omit these costs. By excluding these important but difficult-to-estimate components, we likely underestimate the total cost of pollution-induced crime.

[44]As we note in Section IV, we exclude areas within a mile of more than one interstate, as they might be treated more than once on a given day. We additional exclude regions of the city close to O'hare airport and along Lake Michigan, as unlikely to be representative.

[45]In principle, areas greater than one mile from an interstate might be affected as well.