Air Pollution and Criminal Activity: Evidence from Chicago Microdata

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Abstract

A large and growing literature documents the adverse impacts of pollution on health, productivity, educational attainment and socioeconomic outcomes. This paper provides the first quasi-experimental evidence that air pollution casually affects criminal activity. We exploit detailed location data on over two million serious crimes reported to the Chicago police department over a twelve-year period. We identify the causal effect of pollution on criminal activity by comparing crime on opposite sides of major interstates on days when the wind blows orthogonally the direction of the interstate and find that violent crime is 2.2 percent higher on the downwind side. Consistent with evidence from psychology on the relationship between pollution and aggression, the effect is unique to violent crimes – we find no effect of pollution on the commission of property crime.

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1 Introduction

A large and growing literature documents adverse impacts of air pollution on a wide range of individual outcomes in the short- and long-run. Using a variety of quasi-experimental strategies, the literature documents that pollution harms 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 documenting the first quasi-experimental evidence that air pollution affects violent criminal activity. Building on previous work in economics and medicine, our results suggest that pollution may affect cognition in ways that extend beyond impairing standardized test performance and may influence behavior along dimensions more complicated than those previously considered. Our findings further imply that traditional estimates of the external costs imposed by local air pollution may be understated. Estimates of the direct and indirect annual costs of crime in the U.S. are considerable and of similar magnitude to many of the well-studied impacts of traffic on health considered relevant for cost-benefit analyses – accounting for impacts on criminal behavior would increase externality-correcting Pigouvian pollution taxes.

To estimate the causal effect of pollution on crime, we exploit detailed location data on over two million serious crimes reported to the Chicago Police Department from 2001-2012. Our empirical strategy is straightforward. We focus our attention on major interstates that transect the city of Chicago: I-90, I-94, I-290, I-55 and I-57, which generate substantial local air pollution. 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 south of the road. By comparing relative criminal activity on opposite sides of I-290 on days when the wind is blowing to the south versus the north, we can control for the main threat to panel identification: omitted variables plausibly correlated with both pollution and criminal activity, such as economic activity. The side of the interstate from which the wind blows acts as a control that captures variation in day-to-day

[1] e.g., Schlenker and Walker (2011), Currie and Walker (2011), Beatty and Shimshack (2014), among others
[2] Hanna and Oliva (2015), Zivin and Neidell (2012)
[3] Lavy et al. (2014)
[4] Moretti and Neidell (2011), Zivin and Neidell (2009)

crime, ambient pollution and unobservables, such as neighborhood economic activity.

On days when the wind blows orthogonally to the interstate, we find that violent crime increases by 2.2 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. As further evidence that we are identifying a causal effect of road pollution, we find that the effect of being downwind is attenuated on days when the direction of the wind is not orthogonal to the road and when wind speeds are sufficiently high to disperse pollution. We also consider alternative ”roads” parallel to I-290 as a form of falsification test and find that the downwind estimate is maximized precisely at the latitude at which I-290 transects the Chicago. Finally, we present suggestive evidence that the effect on violent crime is driven by NO_x (or other pollutants that manifest in the warmer seasons) rather than CO. When we allow treatment effect to vary by season, we find that the point estimate of the downwind effect greatest during spring and summer months.

We first discuss summarize the two threads of the literature most relevant to this work: the literature on environmental conditions and crime and the literature on pollution and cognitive impacts. We discuss data in section 3 and in section 4 provide suggestive city-level evidence, by instrumenting for pollution using wind direction and wind speed. In section 5, we examine the micro-geography of criminal activity. Section 6 concludes.

2 Previous Literature

2.1 Environmental Conditions and Crime

There is a long history in the criminology, sociology, and economics literatures focused on the relationship between the prevalence of criminal activity and the surrounding environment. Most closely related to our work, Cohn and Rotton (1997) represents a strand of criminology research in which a time-series of weather is regressed on crime for a single city. They find that violent crimes follow an inverted U-shape as temperatures rise. Jacob et al. (2007) take a panel data approach, using weekly crime and temperature measures for over 100 U.S. cities. They, too, establish that crime is increasing in temperature; additionally, while violent crime decreases with precipitation, property crime is mostly unaffected. 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. In contrast, property crime is lower when it is cold, but does not increase on especially hot days. Similar patterns arise when considering aggressive behavior more broadly as discussed by Hsiang et al. (2013), in countries around the world and at both interpersonal and societal levels (see, e.g., Hsiang et al., 2011; Burke et al., 2009).[5]

In contrast to the research linking temperature to crime, research examining a possible link between pollution and crime rates is limited. Rotton and Frey (1985) estimate a time-series regression based on pollution, temperature, domestic disturbance, and assault data from Dayton, OH. They find that higher ozone levels are related to increased domestic disturbance calls and assaults, though the latter is not statistically significant. In a long-run context, 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.

2.2 Pollution and Cognitive Outcomes

There are three main channels through which one would expect the greater environment to affect criminal activity. First, consider a criminal weighing the costs and benefits of committing a crime, as in Becker's model of rational crime. If it is unpleasant to be outside, this contributes to the cost side if the crime must be committed outdoors. Second, consider a model of crime in which the number of crimes is a function of total interpersonal interactions, i.e., criminal opportunities. If the number of people outside decreases because of environmental factors, this would also reduce crime rates. Third, environmental factors may affect the propensity of a potential criminal to commit crime .

The medical, physicological and economic literatures suggest two pathways by which air pollution might affect behavior: a physiological one, through which air pollution directly affects the central nervous system, and a psychological one, through which air pollution causes discomfort which itself leads to antisocial behavior. Block and Calderón-Garcidueñas (2009) summarizes several hypothesized physiological pathways by which ambient pollution exposure can affect the function of the central nervous system. The first pathway is the direct entry of ultra-fine particulate matter into the brain. Once the particles reach the brain, medical researchers posit two mechanisms for toxicity. The pollutant (or toxic compounds bonded to the pollutant) can affect brain chemistry directly. Ozone, as an example, is a highly reactive substance that reacts with molecules in the body to create toxins. Alternatively, the pollutant

[5] Other documented environmental drivers of crime include rainfall, most commonly by impacting agricultural productivity (see, e.g., Iyer and Topalova, 2014) and ambient light, by impacting the likelihood of detection (Doleac and Sanders, 2012).

may trigger an inflammatory response in the central nervous system. Beurel and Jope (2014) outline a number of studies that link neuroinflammation to increased aggression, impulsivity, and depression.

Finally, air pollution can affect physiology in other ways that impact cognition. As an example, carbon monoxide may directly affect physical and cognitive functioning. CO binds to hemoglobin, thus preventing it from accepting oxygen and contributing to hypoxia. This oxygen deficiency can have deleterious effects on an exposed individual. In a rare controlled lab experiment, Amitai et al. (1998) exposed 45 Hebrew University students to various levels of carbon monoxide. They tested these students, as well as 47 control students, along various neuropsychological dimensions. They found that even low level exposure results in impaired learning, attention and concentration, and visual processing. Although this experiment exposed subjects to higher levels of CO than the ambient levels found in Chicago during our sample period, the results are suggestive of cognitive effects.

Alternatively, pollution may trigger a psychological response. A long literature in psychology hypothesizes and tests the notion that pain and discomfort can induce aggressive behavior (Anderson and Bushman, 2002). Exposure to a variety of pollutants can cause irritation and pain. 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. Further, headaches and head tightness are known symptoms of acute CO exposure. Finally, ambient pollution causes irritation of the eyes and respiratory system. Because of the ethical concerns involved, lab experiments in which human subjects are exposed to pollution are rare. Thus, Rotton (1983) and Rotton et al. (1978) exposed laboratory subjects to malodorous chemicals. The odors were found to reduce cognitive performance, tolerance for frustration, and the subjects' ratings of the quality of other people and the physical environment. The authors hypothesize that this effect is similar to other basic stressors, such as noise.

Regardless of the pathway, papers in both psychology and economics document relationships between air pollution and observable cognitive impairment. A first strand of the literature presents observational evidence that psychological distress is more prevalent on days with high pollution. Rotton and Frey (1984) use data on psychiatric emergencies from the Dayton, OH police department. They find 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) examined the relationship between emergency department visits for depression and ambient air pollution. There were significant positive correlations for 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 a number of different pollutants and suicide, suicide attempts, and suicidal ideation (Lim et al. (2012); Szyszkowicz et al. (2010); Yang et al. (2011)).

In the economics literature, previous research has established a link between pollution and cognitive ability as measured by academic testing. Lavy et al. (2014) analyze student performance on high-stakes Israeli high school examinations. They find that students who take their exam on days with higher $PM_{2.5}$ and CO tend to receive lower scores. The $PM_{2.5}$ pathway appears to be driven at least partially by asthma, but the impact of CO is homogeneous across demographics, suggesting a more fundamental cognitive impact. Sanders (2012) takes a longer-run approach by relating *in utero* exposure to total suspended particulates to later academic performance. He finds that a one standard deviation increase in particulates caused an decrease in test scores of 0.07 standard deviations. Finally, Stafford (2014) exploits the quasi-random timing of school renovations to link indoor air quality and academic performance. She finds that, while attendance is not affected, performance on standardized tests improve after the renovations. The average mold remediation project led to a 0.15 standard deviation improvement in test scores, while the average ventilation project led to a 0.04-0.09 standard deviation improvement. More recent literature extends to alternative measures of cognitive impairment to test scores: Archsmith (2015) finds evidence that baseball umpires make more mistakes when calling strikes on polluted days.

3 Data

3.1 Crime Data

Our crime data come from the City of Chicago's open data portal. The database is drawn from the Chicago Police Department's Citizen Law Enforcement Analysis and Reporting system, and it includes all reported crimes from 2001 to the present. Variables include type of crime, date, time of day, location of the crime (down to the city block), whether an arrest was made, and 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. This class of crimes consists of homicide, forcible rape, robbery, assault, battery, burglary, larceny, arson, and grand theft auto. We further separate 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%).

Crime reports display certain temporal and seasonal regularities. As is clear from Figure 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 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 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 1 and 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 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.

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 need to use short-run variation in the two variables for appropriate causal identification. Second, the seasonality indicates that weather (particularly temperature) is an important variable that must be controlled for flexibly. Third, the clear correlation between crime location and economic activity stresses the importance of a good instrument, because ambient pollution and the location of pollution sources will also be correlated with economic activity and the demographic characteristics of residents of a given neighborhood.

Like other papers that use data on reported criminal activity, our data share shortcomings common with other data sources used in the existing literature documenting criminal activity. We only observe crimes reported to the police, with the exception of homicide. Crimes may be differentially underreported, especially those that are personally sensitive. However, this should only matter if underreporting is directly affected by our instrument. Unless underreporting is correlated with when pollution is blowing into an area, our strategy for causal identification will remain valid. Second, the time stamp of each crime reflects the time at which the crime was reported, rather than committed. As noted above, this might result in some degree of misreporting in terms of the hour (more likely) or the date (less likely). Our empirical specifications will account for this problem, but all estimates will still be conditional on the pattern of reporting found in the data.

3.2 Weather Data

Our weather data is based on data collected by 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.[6]

The construction of our daily wind variables merits discussion. We observe hourly wind speed and direction; because wind direction is circular data, averages are not straightforward.[7] To obtain a daily average wind direction, we first take the angle (in radians) θ, and calculate the u ($\cos\theta$) and v ($\sin\theta$) components of the hourly direction vectors. We average the each component over the hours in a day, and calculate the mean direction as $\arctan(u/v)$.

To calculate average speed and power measures, we take two different approaches, one "vector-based" and one "scalar-based".[8] The vector-based approach weights each hour's u and v components with the speed (or power) observed. The speed/power average is then the norm of the resulting average vector (i.e., $\sqrt{(u^2+v^2)}$). This approach obtains a measure of the average *net* speed or power of the wind. The scalar-based approach takes the simple average of the wind speed (or power) over the hours of the day. In the text, we specify the measure we use in any given context, and provide explanations for why the selected measure is more appropriate. Although the two approaches measure slightly different things, they are nonetheless highly correlated ($\rho \approx 0.9$).

3.3 Pollution Data

Our direct measures of ambient pollution come from the Environmental Protection Agency's network of monitors. In the city-level regressions that follow this section, we take monitors that are located in the Chicago area and are generally operating from 2001-2010. This leaves 4 CO monitors and 2 PM_{10} monitors. For CO, we take a simple daily average over the hourly measurements. Only monitor-days with at least 18 valid hourly readings are included in the sample. In the case of PM_{10}, hourly measurements are not available, so we use the 24-hour average provided by the EPA. To avoid composition problems, we only include days for which all the monitors for a given pollutant have a valid daily average. For CO, these criteria reduce our sample to 3515 days out of a possible 3650. For PM_{10}, the sample is reduced to 3399. As is clear from Table 1, the missing observations are relatively uniformly spread across the months and years for both pollutants. The mean CO and PM_{10} readings vary over the course of the year, as illustrated in Figure 5. PM_{10} emissions are highest during summer months while CO

[6] 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.

[7] For instance, the average direction of an hour during which the wind blows at 1 degree and one during which it blows at 359 degrees is 0 degrees, not 180.

[8] Gilhousen (1987) provides an overview and comparison of the two approaches.

emissions are highest during the winter months, reflecting the different sources of the two pollutants.

4 City-level Crime and Pollution

4.1 Empirical Strategy

We start by establishing a suggestive relationship between pollution and crime at the city level using a time-series variation. In this context, OLS estimates will be vulnerable to a number of sources of bias. Specifically, pollution and crime are both likely to be correlated with seasonal trends, coincident weather conditions and unobservables such as economic activity.

Our empirical strategy is relatively straightforward. To address seasonality and disparities between the weekdays and weekends, we condition on month-of-year and day-of-week fixed effects. Since pollution and crime are both correlated with weather, we flexibly condition on temperature and precipitation using a semi-parametric bin estimator for both. The remaining clear threat to identification is unobserved economic activity.

Days with greater economic activity may increase both pollution and criminal activity, the latter arising because of increased interpersonal interaction. To address this source of bias, we instrument for pollution using wind direction and power. As an illustration of the first-stage, Figures 6 and 7 display contour plots of pollution at one PM_{10} and one CO monitor in our data. 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 Figure 6 illustrates, wind direction in Chicago plays an important role in air quality. As a point of reference, monitor 31-1016-3 is located near to I-55, approximately twelve miles southeast of the city center. Strong winds off of Lake Michigan (blowing from the northeast) lead to low levels of PM_{10} at the inland monitor. In contrast, winds from the southeast and southwest lead to high PM_{10} readings. Approximately fifteen miles to the southeast are the Blue Island refinery and the Arcelor Mittal steel mill. To the southwest are the ExxonMobil Joliet refinery, the Citgo Lemont refinery and Corn Products International wet corn milling operation, all of which generate substantial PM_{10} emissions. This illustrates our general source of identification in the city-level model. The identification strategy is similar spirit to that of Schlenker and Walker (2011), who use wind direction and airport emissions to instrument for ambient pollution in California to estimate causal health effects. We use the vector-based speed and power measures in the city-level regressions, as they better capture the magnitude with which the wind is blowing in the dominant direction.

We estimate the following IV/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 and the interaction of these bins with vector-based average daily wind power. X_t is a vector of controls including 5°C daily maximum temperature bins, 5 total daily precipitation bins, vector-based average wind speed, a first of month indicator, a January 1 indicator, day of week dummies, and month of sample dummies. $Poll_t$ is the average pollution reading across all sample monitors in the city of Chicago, and $Crime_t$ is the total number of (either violent or property) crimes in Chicago on day t. The identification assumption, $E[W_t \nu_t | X_t] = 0$, holds if wind direction and the vector-based wind power-direction interaction only affect crime directly through the pollution moved in or out of the city. Wind direction and vector-based power-direction interactions are plausibly correlated with other weather variables or seasonal variables that affect crime. After conditioning on temperature, precipitation and seasonality, the remaining threat to validity is if the wind itself directly affects crime. We control for the vector-based wind speed in the second stage regression, leaving wind direction as the only plausible source of contamination. That is, our identification assumption may not hold if wind off of Lake Michigan (for example) affects criminal behavior differentially than wind blowing from the west, controlling for wind speed, temperature, and precipitation. In robustness checks, we also allow the interaction of temperature and vector-based wind speed to enter the second stage regression.

4.2 Results

Table 2 displays the results from the city-level CO regressions. The first column is a simple OLS regression of the logarithm of violent crime on mean daily average CO concentration and a set of controls. The signs on the controls make sense: higher temperatures are associated with more violent crime, more precipitation is associated with less, and the first of month and January 1 indicators soak up the reporting anomalies or any "first of the month" effect (Foley, 2011). However, the main effect of pollution on crime is negative and not statistically significant. In column 2, we turn to our IV strategy. The estimates on the controls are essentially unchanged, but now the effect of CO on violent crime is positive and significant at the 5% level. Moving from the median CO day to the 90th percentile (0.5 ppb increase) is associated with nearly 5% more violent crime. The analogous effect on property crime is statistically insignificant and small. This discrepancy across crime types may suggest that the primary mechanism is physiological; that is, the pollution might make people more irritable and impulsive, thus leading to more violent crime. The first stage regressions are not weak: the F-statistics are approximately 19.

Table 3 displays the results from the city-level PM_{10} regressions. The first column is a simple OLS regression of the logarithm of violent crime on mean daily average PM_{10} concentration and a set of controls. The coefficient estimates on the controls are very similar to those from the CO regressions. Again, the OLS estimate on violent crime is smaller in magnitude than the IV estimates, although the OLS estimate is actually positive and statistically significant in this case. The IV estimates are significant at the 10% level, and translate into nearly 3% more violent crime on a 90th percentile PM_{10} day compared with a median day. Again, the property crime estimates are statistical zeros. The first stage is quite strong in this case: the F-statistics hover around 30.

These city-level regressions suggest a causal relationship running from pollution to violent crime. As a point of comparison, the 5% increase in violent crime from a high-CO day is comparable to the estimated effect of moving from the 25-30°C (77-86°F) maximum temperature bin to the 30-35°C (86-95°F) bin (7% increase in violent crime). That is, the increase in violent crime when moving from a typical CO day to a high-CO day is comparable to the increase associated with moving from a warm day to a hot day. Still, these results are based on time-series variation. At the level of a metropolitan area, especially one near a lake, using average weather and pollution data could introduce considerable measurement error. Thus, we now turn to a more localized approach that exploits the very detailed location associated with each crime.

5 The micro-geography of pollution and crime

While the city-level regressions provide suggestive evidence of the relationship between pollution and crime, 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.

To provide more compelling 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 using *within-day* variation in pollution and criminal activity, by comparing local regions within the city of Chicago. As a result, we are able to flexibly control for day-to-day unobservables correlated with crime that we might be concerned would bias city-level estimates.

To motivate the identification strategy, consider Figure 7, which summarizes CO readings at one of the monitors in our city-level data (31-6004-1). This monitor is located immediately north of I-290, which runs due East/West from the Chicago city center to the suburbs of Oak Park and Berwyn. Like Figure 6, 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, but not dominantly enough to carry the emissions beyond the nearby neighborhood. Conveniently, immediately across the highway from the monitor are several cemeteries that occupy an area extending approximately one mile south of I-290 and a quarter mile east and west of the location of the pollution monitor. Consequently, we attribute the incremental pollution at the monitor when the wind is blowing from the south to the pollution from traffic on I-290.[9]

Our identification strategy is easiest to explain again using I-290 as an example. I-290 runs (essentially) due west from Chicago. 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. This approach better addresses the identification concerns arising with the city-level analysis. 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. 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 a similar identification strategy to the other expressways in the Chicago area by examining crimes within one mile of major interstates on days during which the wind is blowing orthogonally to the direction of the interstate. Figure 8 plots the location of all crimes in Chicago within one mile of any interstate. For the analysis, we limit the sample of crimes to

[9]Carbon monoxide emissions from mobile sources account for the majority of anthropogenic CO emissions in the U.S. The National Emissions Inventory in 2011 reports that mobile sources generated 92 percent of carbon monoxide emissions in Cook County, 80 percent in Illinois, and 50 percent nationally (75 percent, excluding fires). Source: http://www.epa.gov/cgi-bin/broker?polchoice=CO&_debug=0&_service=data&_program=dataprog.national_1.sas.

the colored regions in Figure 8 based on several criteria. First, we drop crimes that are within one mile of more than one interstate. These locations may be downwind of more than one interstate at a given time and create the possibility for very complicated treatment effects. This 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 we exclude is proximate to and includes Chicago O'Hare International Airport – criminal activity near an airport is unlikely to be representative of criminal activity elsewhere, and the airport itself is a significant source of pollution. The southeastern part of the city borders Lake Michigan to the east and Lake Calumet to the southwest; the lakes differentially affect the possibility of criminal activity on the relevant 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.

For a basic specification, we examine crimes within one mile of either side of the interstate and on days during which the average wind direction is within sixty degrees of the line orthogonal to the direction of the interstate.[10] Thus, for I-290, running east and west, we focus on days for which the wind blows from a direction between 300 degrees (roughly NW) and 60 degrees (roughly NE) or from a direction between 120 degrees (roughly SE) and 240 degrees (roughly SW). We relax both of these assumptions in robustness checks.

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. 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 each class of crimes. Interstate-side fixed effects (α) control for time-invariant unobservables that are correlated with criminal activity on each side of the interstate. In contrast, the interstate-date fixed effects (γ) control for daily variation in criminal activity near each interstate.

Exploiting the micro-geography of Chicago allows us to address the main identification concern with the city-level analysis. Effectively, the upwind side of the interstate acts as a con-

[10]For I-90, which travels northwest then north and then northwest again, we treat each of the three segments of the interstate separately.

trol for day-to-day variation in local criminal activity. We identify the effect of being downwind from the interstate by comparing criminal activity on opposite sides of the interstate on days when one side is downwind and days when the other side is downwind.

5.1 Main Results

We present the results for violent crime in Tables 4. column 3 corresponds to the specification in equation (3).[11] We find that the downwind side of the interstate experiences 0.023 more violent crimes per day. When measured relative to the mean number of violent crimes (1.09 per route-side per day), this represents an increase of approximately 2.2 percent.

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. Using 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 that 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.

We do not think this threat to identification is likely to bias our estimates. The seven interstate segments we examine transect different parts of the city of Chicago with different socio-economic characteristics. Furthermore, the interstate segments travel in different directions. To bias our estimates, such stories like the one in the preceding paragraph 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. In column 4, we allow for the number of crimes on each of the fourteen interstate sides to vary independently with temperature and precipitation. Going forward, we take this as our preferred specification. Formally, column 4 estimates:

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

where X_{ist} includes the maximum temperature over the course of the day and precipitation over the course of the day.

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 temper-

[11] We also present estimates from very parsimonious specifications in columns 1 and 2 for the purpose of additional comparison.

ature and precipitation, our estimates are almost identical: the downwind side again experiences 0.023 more violent crimes per day, an increase of approximately 2.2 percent relative to mean violent crime levels.

Table 5 presents the results of identical specification for property crime rather than violent crime. As in the city-level analysis, we find little evidence that pollution impacts property crime. In none of the specifications is the downwind side of the interstate associated with an increase (or decrease) in property crime. In fact, the point estimates are smaller in magnitude than those for violent crime, despite the much larger baseline incidence of property crime.

5.2 Testing the mechanisms

Crime subcategories Although it is convenient to examine aggregated violent and property crimes, there are substantial differences in the natures and costs of the different crimes. We can further disaggregate the data and estimate effects for the individual index crimes. In doing so, we sacrifice power – especially among the rarer crimes such as homicide. Still, the results are informative.

Table 6 presents the results of estimating our preferred specification separately for the various violent crimes in our data. We estimate 7.8 and 3.4 percent increases in rape and homicide, respectively, but these are not significantly different from zero. The estimated increase in violent crime appears to be driven by aggravated battery arrests. At the same time, the number of aggravated assault arrests decreases. An assault is 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." A battery is 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."[12]. That is, a battery subsumes an assault in the case that actual bodily injury is sustained. 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.

Breaking down the property crime (Table 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.

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

Seasonality and specific pollutants It is important to note that we identify the effect of being downwind of an interstate on violent crime, but cannot definitively distinguish among the effects of CO emissions, NO_x emissions or other emissions generated by mobile sources. This is a common challenge to much of the literature on pollution and outcomes. Since emissions of different pollutants are often highly correlated, it is difficult to empirically distinguish the effect of the specific pollutants.

Although it is not a definitive approach, we can leverage the fact that the emissions profile for mobile sources tends to change over the course of the year. Carbon monoxide emissions arise from incomplete combustion and insufficiently-warm catalytic converters, both of which are greater problems during cold-weather operation. In contrast, NO_x emissions from vehicles tend to be greatest during summer months – NO_x emissions from mobile sources form at extremely high combustion temperatures, most commonly when engines operating at high temperatures are unable to cool down sufficiently.

As indirect evidence of the impact of specific pollutants, we allow for the treatment effects in Table 4 to vary by season. We report the coefficient for the season-specific treatment effects in Table 8. 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 2.2 percent increase in violent crimes observed over the entire year, being the downwind side of the interstate is associated with a four to six percent increase in violent crime in the spring/summer. In contrast, the winter and fall treatment effects are not statistically distinguishable from zero in all but the first specification. Although not dispositive, the seasonal treatment effects are consistent with the conclusion that NO_x (or other summer-specific mobile emissions) are the primary channel influencing the commission of violent crime.

Effect of wind speed A natural extension of our main result is to relate the treatment effect to the wind speed. In these specifications, we are particularly interested in how wind speed affects pollution transport and dispersion in a very local sense. To capture this, we use the scalar-based wind speed measure to understand how the treatment effect varies when pollutants are more or less locally-dispersed in the neighborhood of the highway. This is a more appropriate measure than the vector-based approach, which captures the net *magnitude* of the wind direction.

To get a sense of what we should expect, consider Figure 10. This figure is analogous to Figure 7 in that it shows pollution at the CO monitor just north of I-290, except that the radial dimension now represents scalar-based wind speed, rather than vector-based (or net) wind speed. On extremely calm days, there is very little wind-driven pollution dispersion. Thus, the monitor reading is very similar no matter what the average wind direction is. As the wind speed increases, the pollution reading decays quickly if the monitor is upwind, but more gradually if the monitor is downwind.

We bin days based on the scalar-based wind speed for that day. The bins are 2 m/s wide, and correspond to the concentric circles in Figure 10. The regressions in Table 10 interact the downwind treatment with the wind speed bins. The effect is largest on days when the wind is blowing lightly, and almost zero on stagnant days. This is very consistent with the pollution pattern in Figure 10. Although stagnant days (those in the smallest circle) are highly polluted, the *difference* in pollution exposure on the upwind and downwind sides of the interstate is small. On days in the second-smallest circle, the downwind neighborhood is exposed to significantly more pollution than the upwind neighborhood. The effect grows again as the wind picks up, but these are imprecisely estimated as such days are relatively rare.

These results bolster the case for a causal relationship between pollution and violent crime. At the same time, they underscore the importance of interpreting the magnitude of our estimates as a reduced form relationship, as measuring the exact difference in pollution treatment is not straightforward.

Day of week Another way to gain some insight into the mechanism behind our estimates is to consider the average behavior of Chicago residents on a given day. In particular, behavior is notably different on weekends than on weekdays.[13] People may be more likely to spend time inside away from their own neighborhood on weekdays.

We interact our downwind treatment with whether a sample day is a weekday or a Saturday/Sunday and re-estimate our model. The results are presented in Table 9. The treatment effect is consistently driven by increased violent crime on weekends. While it is difficult to draw clear-cut conclusions from this result, thinking about a simple model of crime can be informative. Routine Activity Theory, originally established by Cohen and Felson (1979), posits that crime rates are a function of a motivated offender, a suitable target, and the absence of a capable guardian. The biological mechanism we propose primarily acts by increasing the prevalence of motivated offenders. If more people are outside on weekends than weekdays, this effect could be amplified by creating more motivated offenders and more suitable targets. Furthermore, people living in neighborhoods close to interstates may work in another loca-

[13]Note that we do include date fixed effects in all of our main specifications. The main treatment effect is *not* identified off of differences in pollution and crime on weekends versus weekdays.

tion during the week, introducing measurement error into treatment effect and attenuating the effect of pollution on crime.

5.3 Robustness checks

Wind angle and window size Two subjective choices underlie our analysis in Table 4. First, when constructing the sample, we include any day in which the wind blows within at least 60 degrees of the vector orthogonal to the direction of the road. Second, when counting the number of crimes, we include crimes within one mile of either side of the interstate. We relax both assumptions and find that our estimates of the downwind effect vary as we would expect.

Table 11 presents the results of estimating Equation (3) as we vary the two inclusion rules. Each row-column "cluster" of numbers is the treatment effect coefficient, its robust standard error, the number of observations, and the R^2 from a separate regression. We use our preferred specification, column 4 from Table 4, but the results are similar for the specifications for column 3 of that table as well. Moving from left to right, we increase the number of degrees around the orthogonal vector to the direction of the road from 30 degrees to 90 degrees. Moving from top to bottom, we increase the size of the collar around the interstate from one-quarter mile to one-half mile to one mile. Our main specification (60 degrees, one mile) is in bold.

As an illustration of the angle inclusion rule, consider areas near I-290, which runs due east-west. In column 1, we would only include days in our estimation during which the wind blows between 330 degrees and 30 degrees or between 150 degrees and 210 degrees.[14] In contrast, in column 5, we would include all the days in the dataset – any day during which the wind blew in a northerly direction would be considered a day in which the north side of the road was treated and the south side was not.

As the table illustrates, extending the angle inclusion rule has two effects. First, increasing the angle used for inclusion increases the size of the sample and the precision of the estimates. Moving from left to right across the table, standard errors monotonically decline. Second, increasing the angle for inclusion broadens the set of days during which we consider the north side of the road treated. Consider, for instance, the most inclusive rule, column 5. In the case of I-290, if, on a day, the wind blows towards 271 degrees, one degree north of due west, we consider that day a day on which the treatment applies to the north side of the road, despite the fact that pollution from I-290 would likely affect both the north and south sides of the interstate.

[14] In the case of I-290, the vector orthogonal to the direction of the road runs essentially north-south.

Increasing the inclusion angle tends to attenuate the point estimate of the downwind effect; 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.[15] The estimates increase less than linearly with the size of the band, up to one mile, suggesting that the effect of being on the downwind side diminishes slightly with distance from the interstate.

Lagged crime and wind direction Next, we address the possibility that our results are driven by short-run autocorrelation. If wind direction and crime are both correlated over time, then we would expect to see a relationship between them. Indeed, this dynamic process is the primary focus of Jacob et al. (2007). To address this concern, we again re-estimate our preferred specification, but include up to three lagged days of crime and treatment status. Table 12 shows that while crime does demonstrate positive autocorrelation, controlling for lagged crime and wind has only a very small effect on our estimates. In particular, we only find evidence that contemporaneous wind direction and pollution affect criminal activity on a given day.

Alternative identification approach To further test the robustness of our main results, we exploit a different source of variation induced by the wind. In the main specification, we included route-side and route-date fixed effects. Thus, our estimates came from the response of crime in a given neighborhood to being downwind, relative to the corresponding upwind neighborhood on the same day.

In this alternative specification, we essentially use crime (and average wind exposure) at a location on the same day of the year in other years as a control for crime at the location on the day of interest. That is, when a given route-side is more consistently downwind on July 10th, 2011 than on the typical July 10th, do we see higher violent crime on that day? In the first three columns, the treatment variable calculates the fraction of the day the wind was blowing to that side of the road. In the last three columns, the treatment is continuous: the wind blowing directly towards one side is a stronger treatment than wind blowing at an angle to the vector of orthogonality. The sample size is larger than the main specification because we are able to use all days in our data, rather than restricting our sample to only the days in which the wind is blowing orthogonally to the interstate on average.

Table 13 presents the results. On a day that is "unusually downwind" for that calendar

[15] While nothing prevents extending the band beyond one mile to either side of the interstate, the bands around the sections of the interstate used in the main specification begin to overlap.

date, a neighborhood experiences more violent crime. For a given route-side, a completely upwind day will have 0.03 more violent crimes than a completely downwind day using the binary treatment variable. The continuous treatment variable ranges from -1 to 1, so it predicts that a completely upwind day will have roughly 0.035 more violent crimes than a completely downwind day.

These signs and magnitudes are remarkably similar to those in our main specification, even though the exogenous variation in wind exposure is coming from a comparison with different implicit control groups. We take this as evidence that our main causal result is not simply an artifact of our primary specification.

Falsification test As a final piece of evidence, we consider a falsification test of our identification strategy. To motivate the falsification 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 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 falsification test, we focus on the band of crimes at similar longitudes to the crimes in our sample set for I-290, but extending far north and south of I-290. Figure 11 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 with which we conduct a t-test equivalent to the main specification in equation (3). For each latitude, we calculate the daily difference in violent crimes one mile north of the latitude and one mile south of the latitude. We then test whether the differential at that latitude is greater on days when the wind blows north than when the wind blows south.

Figure 12 plots the difference in the north-south violent crime differential on days when the wind is blowing to north rather than the south at each alternative latitude, adjusted for the fact that when the wind is blowing to the south, the pollution "treatment" applies to the southern-side of the latitude. The interpretation is identical to the interpretation of the downwind treatment in column 3 of Table 4, although this exercise only examines one of the seven interstate segments.

Three points in particular stand out in Figure 12. 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 slightly of I-290, we find the lowest estimated value for the downwind effect. When we consider an alternative latitude just north of I-290, winds from the south blow pollution from the road onto the *south side* of the alternative latitude and reverse the sign of the downwind effect. Relative to the alternative latitude, pollution is from I-290 falls on the upwind side. The sharp rebound at latitudes just north of the minimum estimated downwind effect is also reassuring. This suggests that the source of pollution is very local to the latitude at which I-290 cuts through Chicago from east to west and disperses at latitudes further north. Finally, the second highest peak on the graph (at a latitude of roughly 41.84) is on the northern side of I-55 as it exits the sample region of the falsification test.

5.4 Implications for the cost of mobile pollution

Although we estimate that the effect of mobile pollution on crime is modest in magnitude, the annual aggregate costs of crime are significant. Estimates from the literature vary with respect to magnitudes: 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 (e.g., Anderson, 1999) estimates the aggregate cost of crime at over one trillion dollars annually.

Having estimated the causal effect of mobile pollution on crime, we compute a back-of-the-envelope estimate of the cost of pollution-induced crime. McCollister et al. (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.[16]

In constructing our sample, we omit 48% of the crimes that occur within one mile of an interstate.[17] However, in calculating the total cost of pollution, we want to include these areas.[18] If we assume that each of the classes of violent crimes increase according to the estimates from

[16]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.

[17]As we note in section 5, 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.

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

Table 6, 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. In comparison, Currie and Walker (2011) produce a back-of-the-envelope estimate that pre-term births due to traffic congestion carry costs of $444 million per year. Clearly, the costs of mobile pollution-induced violent crime are of a magnitude similar to that of more commonly studied adverse outcomes.

6 Conclusion

In this paper, we provide the first quasi-experimental evidence that air pollution affects violent criminal activity. Our results suggest that pollution may affect cognition in ways that extend beyond impairing performance on standardized tests and may influence individual behavior in more subtle ways that previously considered. Furthermore, our results suggest that the external costs of pollution may be greater than previously estimated - implying optimal policy should more stringently regulate air pollution. We estimate that the downwind side of interstates experience 2.2 percent more violent crimes than when the wind is blowing in the opposite direction. Although we estimate that the effect of pollution on crime is modest in magnitude, our conservative back-of-the-envelope calculations suggest that the cost of mobile pollution-induced crime in the United States is on the order of $100-200 million annually. This magnitude is comparable to many of the well-studied impacts of traffic on health, and should be considered in relevant cost-benefit analyses.

These estimates are particularly important in light of the dramatic decrease in urban air pollution experienced in the United States over the past several decades. Annual peak carbon monoxide readings in Chicago fell by two-thirds between 1990 and 2010 from 6 parts per million to 2 parts per million.[19]. As a rough estimate of the magnitudes of the effect size, in our city-level regressions we estimate a 1 ppm increase in CO is associated with a 0.111 increase in the log of daily crime. Interpreted in a partial equilibrium, the effect size of the decline in pollution on crime in the most polluted hours of the year is considerable.

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[19] Reported carbon monoxide readings based on the 2nd highest annual 8-hour average. Source: http://www.epa.gov/airtrends/carbon.html

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7 Figures

Figure 1: Crime share by hour of day

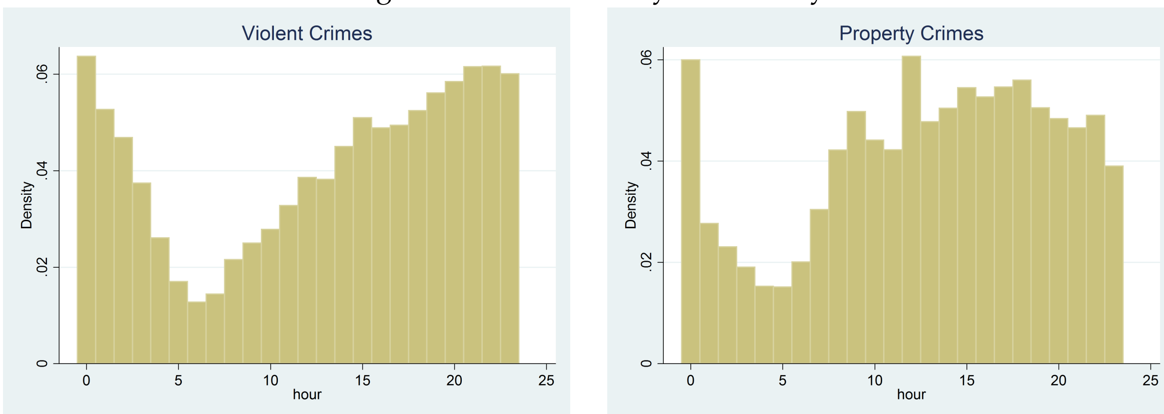


Figure 2: Average crimes by week of year

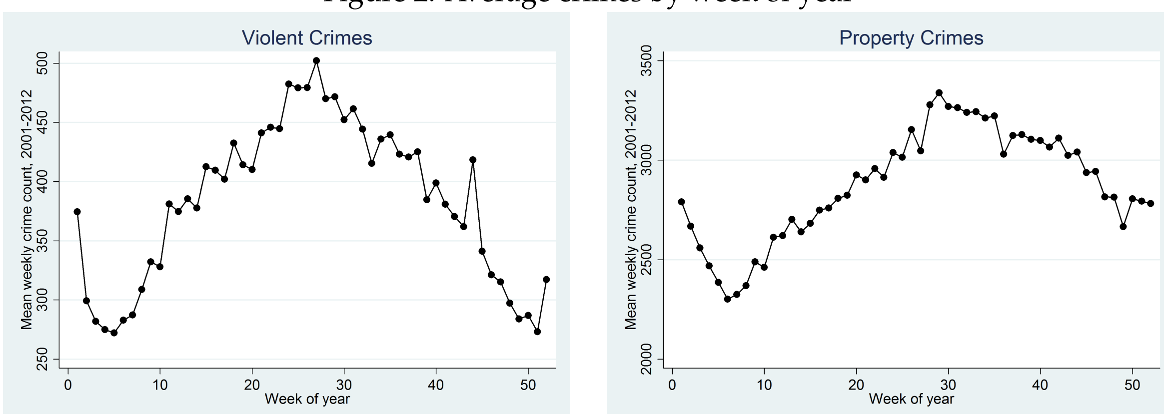


Figure 3: Normalized average annual crimes (2001 levels = 100)

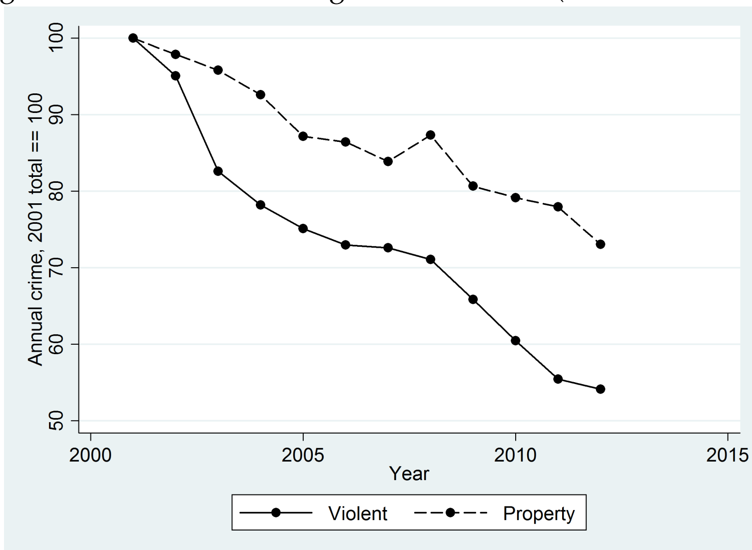


Figure 4: Crime density heat maps

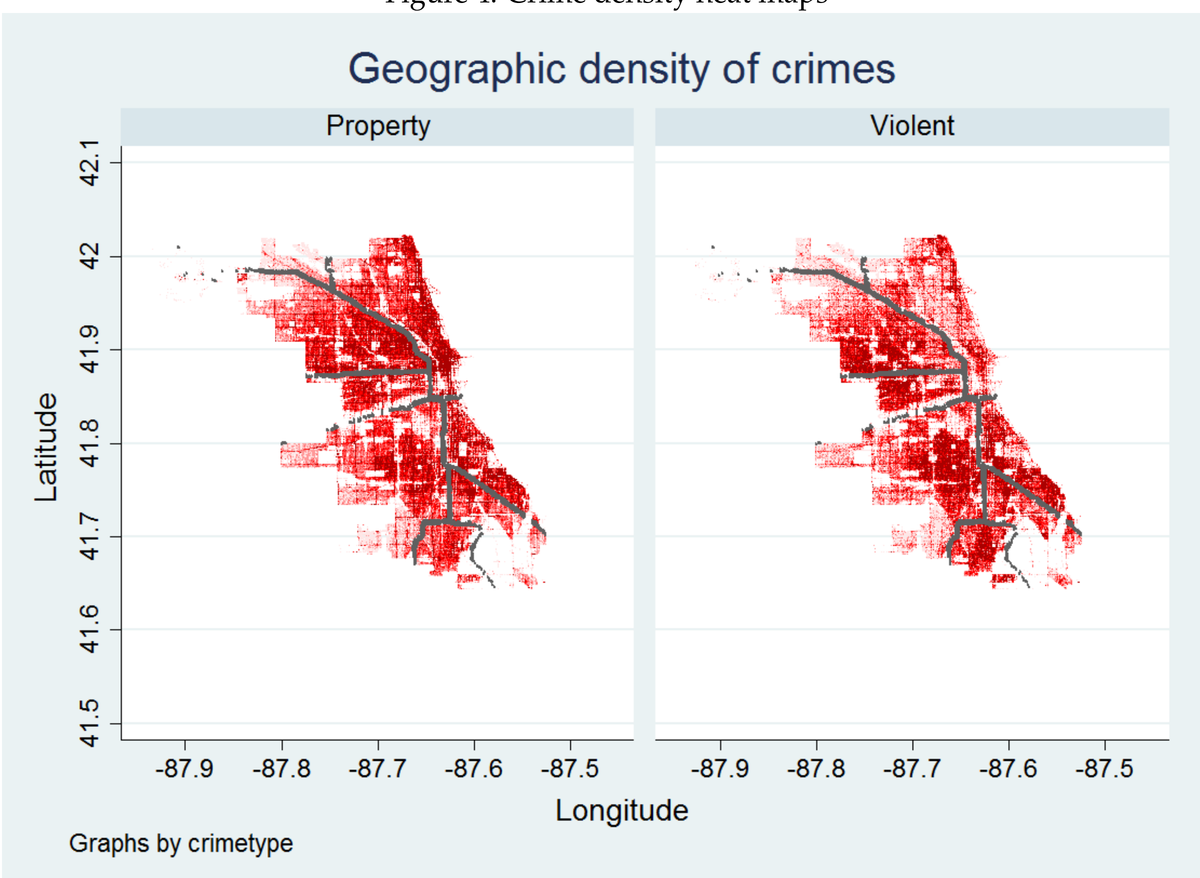


Figure 5: Seasonality in CO and PM_{10} emissions

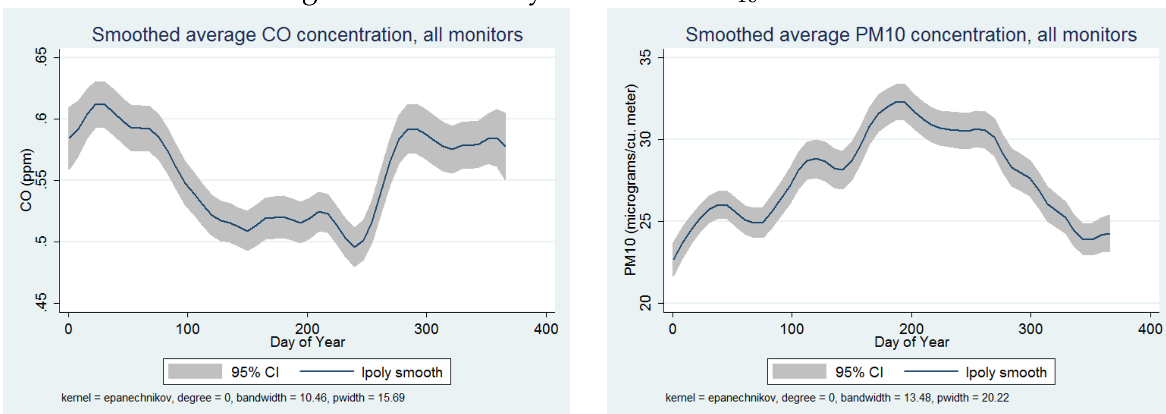


Figure 6: Average PM10 reading as a function of wind direction and vector-based speed

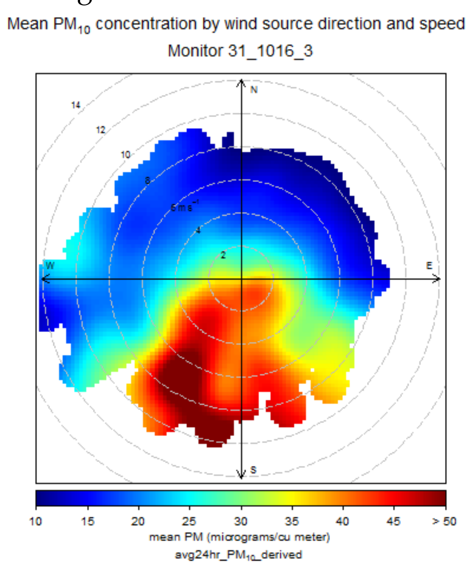


Figure 7: Average CO reading as a function of wind direction and vector-based speed

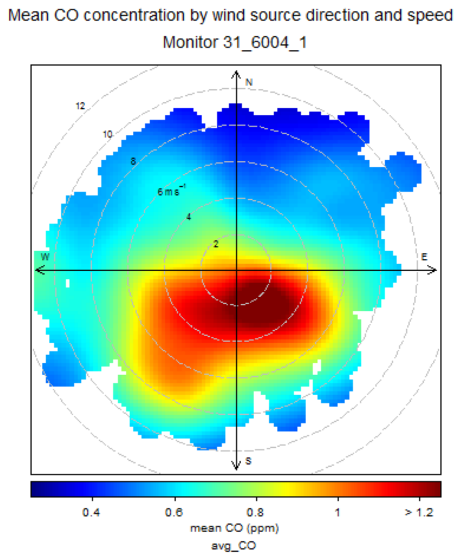


Figure 8: Sample set for interstate identification strategy

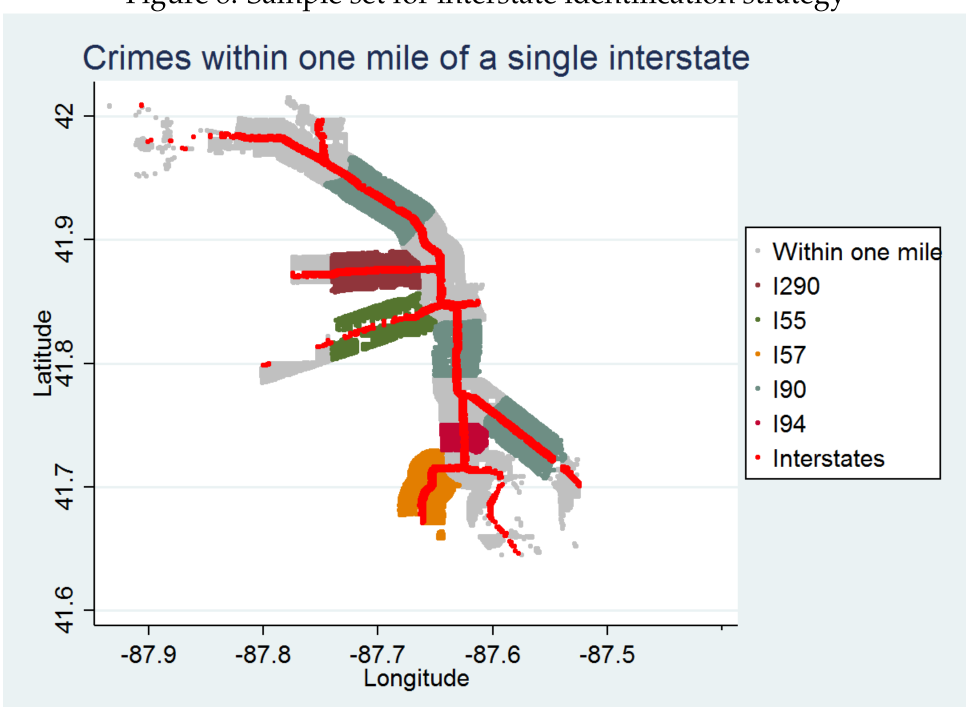
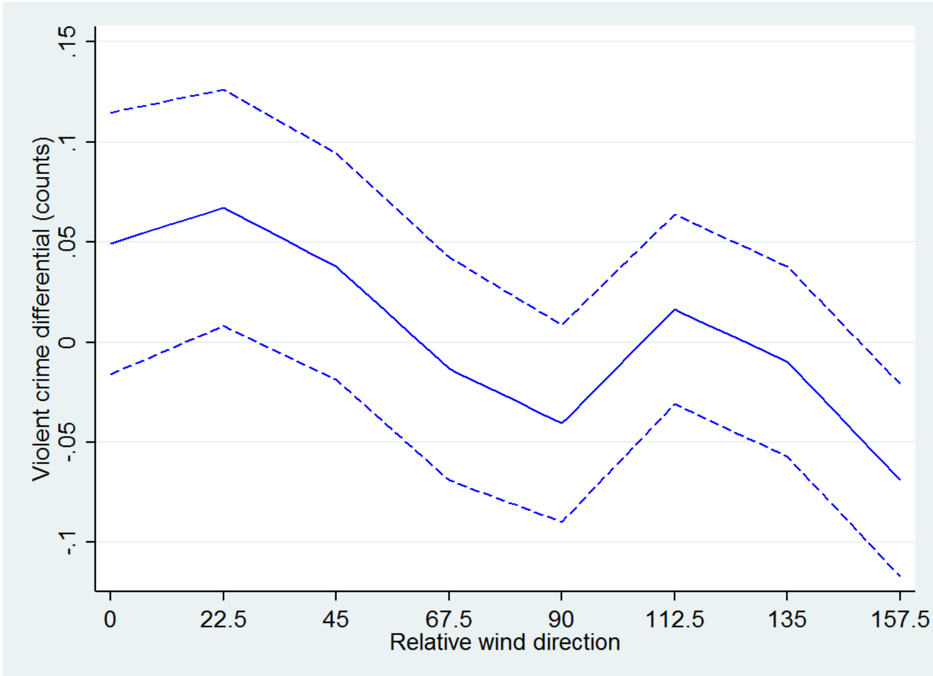


Figure 9: Difference in violent crime, by relative wind vector



Note: Relative wind direction reflects the difference between the wind direction and the vector orthogonal to interstate direction. For example, I290 runs straight East / West. A value of 0 corresponds to a northernly wind. A value of 45 would correspond to a northwesterly or northeasterly wind. Point estimates are denoted with the solid line. 95% CI is denoted by the dashed line.

Figure 10: Average CO reading as a function of wind direction and scalar-based speed

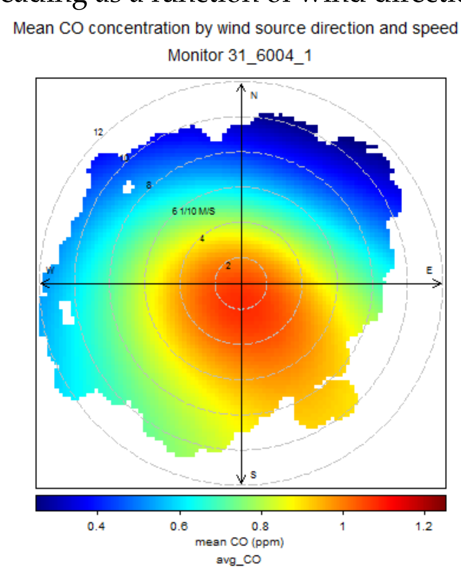


Figure 11: Sample set for falsification test

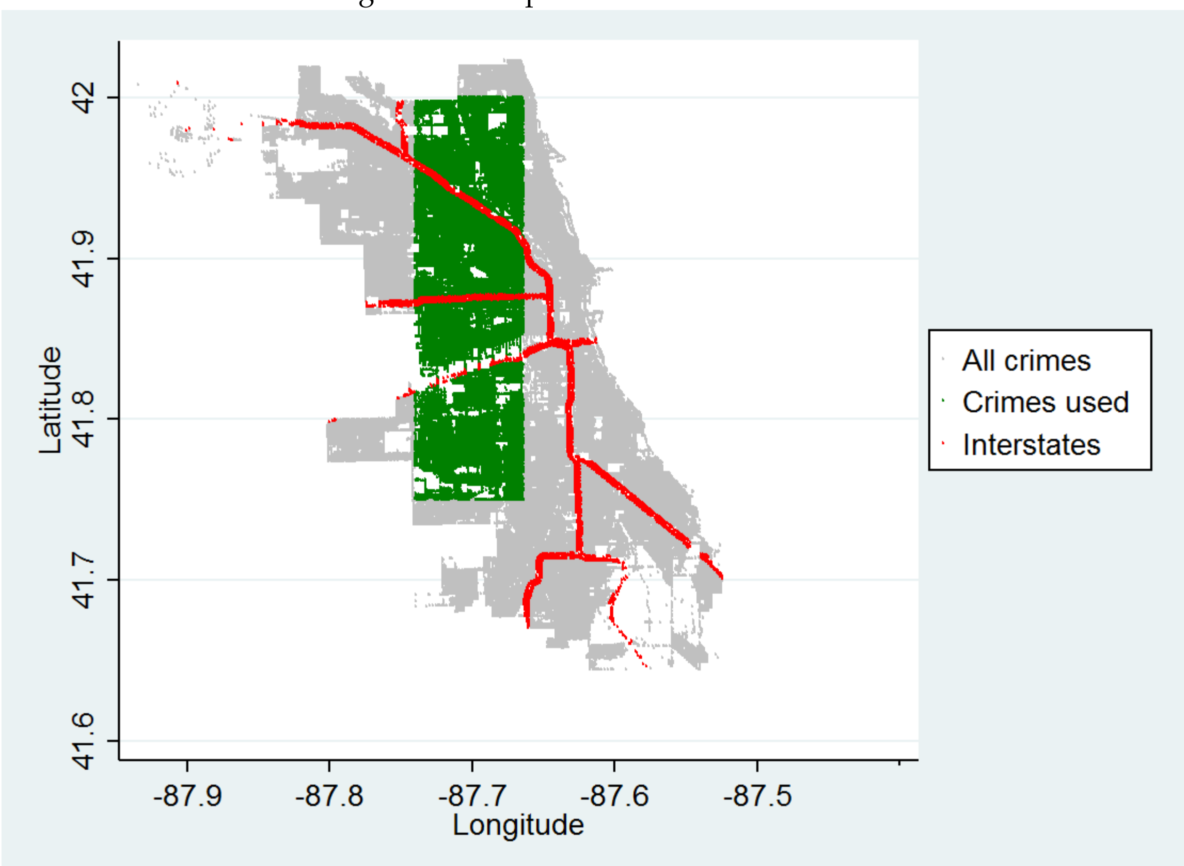
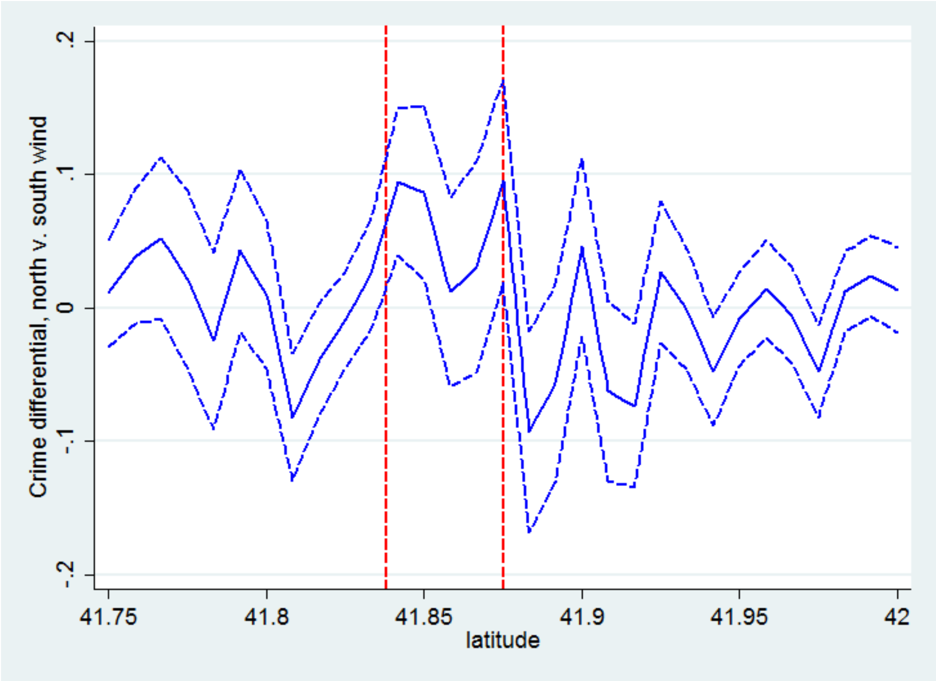


Figure 12: North-south crime differential, alternative latitudes



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: Valid pollution observations by month and by year

CO				PM_{10}			
Month	Avg. Obs.	Year	Obs.	Month	Avg. Obs.	Year	Obs.
January	29.3	2001	350	January	26.7	2001	335
February	27.9	2002	362	February	23.5	2002	324
March	29.1	2003	354	March	29.1	2003	341
April	29.3	2004	353	April	28.0	2004	333
May	28.7	2005	355	May	28.1	2005	340
June	28.0	2006	348	June	29.1	2006	348
July	28.6	2007	344	July	30.1	2007	352
August	30.2	2008	352	August	30.4	2008	363
September	29.4	2009	358	September	29.3	2009	317
October	30.6	2010	339	October	27.7	2010	346
November	29.7			November	29.0		
December	30.7			December	28.9		
Total	351.5		3515		339.9		3399

Table 2: CO impact on daily log crime, 2001-2010

	(1) OLS Violent	(2) 2SLS Violent	(3) 2SLS Diff ≤ 1 C	(4) OLS Property	(5) 2SLS Property	(6) 2SLS Diff ≤ 1 C
Mean of 4 monitors' average daily CO	-0.016	0.094**	0.11**	0.011	0.010	0.0093
	(0.023)	(0.045)	(0.047)	(0.011)	(0.020)	(0.020)
Speed norm of avg. wind vector	-0.00055**	-0.000015	0.000067	0.000073	0.000070	0.000047
	(0.00023)	(0.00029)	(0.00031)	(0.000090)	(0.00013)	(0.00013)
Max temp (-5,0) deg. C	0.085***	0.084***	0.083***	0.056***	0.056***	0.056***
	(0.024)	(0.024)	(0.027)	(0.012)	(0.011)	(0.013)
Max temp (0,5) deg. C	0.18***	0.18***	0.18***	0.10***	0.10***	0.10***
	(0.027)	(0.026)	(0.029)	(0.015)	(0.014)	(0.016)
Max temp (5,10) deg. C	0.25***	0.25***	0.25***	0.13***	0.13***	0.13***
	(0.025)	(0.024)	(0.027)	(0.016)	(0.016)	(0.018)
Max temp (10,15) deg. C	0.35***	0.34***	0.34***	0.16***	0.16***	0.16***
	(0.027)	(0.026)	(0.029)	(0.017)	(0.016)	(0.018)
Max temp (15,20) deg. C	0.43***	0.42***	0.42***	0.16***	0.16***	0.17***
	(0.027)	(0.027)	(0.029)	(0.016)	(0.016)	(0.018)
Max temp (20,25) deg. C	0.54***	0.53***	0.53***	0.16***	0.16***	0.16***
	(0.029)	(0.028)	(0.031)	(0.017)	(0.017)	(0.019)
Max temp (25,30) deg. C	0.62***	0.61***	0.61***	0.17***	0.17***	0.17***
	(0.030)	(0.029)	(0.032)	(0.017)	(0.017)	(0.019)
Max temp (30,35) deg. C	0.69***	0.67***	0.68***	0.17***	0.17***	0.18***
	(0.030)	(0.030)	(0.033)	(0.018)	(0.018)	(0.020)
Max temp > 35 deg. C	0.69***	0.66***	0.66***	0.20***	0.20***	0.18***
	(0.044)	(0.043)	(0.050)	(0.023)	(0.023)	(0.023)
Precip. bin 2	-0.024***	-0.022***	-0.022***	-0.00047	-0.00048	-0.00052
	(0.0080)	(0.0079)	(0.0084)	(0.0043)	(0.0042)	(0.0045)
Precip. bin 3	-0.064***	-0.062***	-0.061***	-0.0045	-0.0045	-0.0051
	(0.010)	(0.010)	(0.011)	(0.0052)	(0.0052)	(0.0054)
Precip. bin 4	-0.12***	-0.12***	-0.13***	-0.010	-0.010*	-0.012*
	(0.015)	(0.014)	(0.015)	(0.0062)	(0.0060)	(0.0065)
Precip. bin 5	-0.15***	-0.15***	-0.15***	-0.029***	-0.029***	-0.028**
	(0.025)	(0.024)	(0.024)	(0.011)	(0.010)	(0.011)
Year*Month FE	X	X	X	X	X	X
Day of Week FE	X	X	X	X	X	X
First Stage F-Stat		19.0	18.8		19.0	18.8
Observations	3467	3467	3231	3467	3467	3231
R-Squared	0.75	0.75	0.75	0.78	0.78	0.78

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered on the month of sample. Dependent variable is the daily citywide crime count. Excluded instruments are 20 degree bins for daily average wind direction at Midway Airport, and a measure of the net daily average wind power vector. Regression also includes first-of-month and first-of-year dummies. CO is the mean over monitors 31-63-1, 31-4002-1, 31-3103-1, and 31-6004-1.

Table 3: PM_{10} impact on daily log crime, 2001-2010

	(1) OLS Violent	(2) 2SLS Violent	(3) 2SLS Diff $\leq$ 1 C	(4) OLS Property	(5) 2SLS Property	(6) 2SLS Diff $\leq$ 1 C
Mean of 2 monitors' average daily PM10	0.00090***	0.0012*	0.0013*	0.000051	-0.000019	0.000060
	(0.00031)	(0.00066)	(0.00069)	(0.00016)	(0.00030)	(0.00031)
Speed norm of avg. wind vector	-0.00035*	-0.00032	-0.00033	0.000011	0.0000050	-0.0000013
	(0.00020)	(0.00021)	(0.00022)	(0.000089)	(0.000090)	(0.000092)
Max temp (-5,0) deg. C	0.11***	0.11***	0.11***	0.057***	0.057***	0.059***
	(0.025)	(0.024)	(0.026)	(0.013)	(0.012)	(0.014)
Max temp (0,5) deg. C	0.21***	0.21***	0.21***	0.10***	0.10***	0.10***
	(0.029)	(0.029)	(0.030)	(0.017)	(0.016)	(0.018)
Max temp (5,10) deg. C	0.28***	0.28***	0.28***	0.13***	0.13***	0.14***
	(0.026)	(0.026)	(0.027)	(0.018)	(0.017)	(0.020)
Max temp (10,15) deg. C	0.36***	0.36***	0.36***	0.16***	0.16***	0.16***
	(0.027)	(0.027)	(0.028)	(0.018)	(0.018)	(0.020)
Max temp (15,20) deg. C	0.44***	0.44***	0.44***	0.17***	0.17***	0.17***
	(0.028)	(0.028)	(0.030)	(0.018)	(0.018)	(0.021)
Max temp (20,25) deg. C	0.54***	0.54***	0.54***	0.17***	0.17***	0.17***
	(0.030)	(0.030)	(0.032)	(0.019)	(0.020)	(0.022)
Max temp (25,30) deg. C	0.61***	0.61***	0.60***	0.17***	0.17***	0.17***
	(0.031)	(0.034)	(0.036)	(0.019)	(0.021)	(0.024)
Max temp (30,35) deg. C	0.67***	0.66***	0.66***	0.18***	0.18***	0.18***
	(0.034)	(0.040)	(0.043)	(0.021)	(0.024)	(0.028)
Max temp > 35 deg. C	0.66***	0.65***	0.64***	0.21***	0.21***	0.19***
	(0.046)	(0.054)	(0.061)	(0.025)	(0.031)	(0.032)
Precip. bin 2	-0.016*	-0.015*	-0.016*	-0.00016	-0.00032	-0.00058
	(0.0085)	(0.0082)	(0.0087)	(0.0044)	(0.0042)	(0.0045)
Precip. bin 3	-0.052***	-0.051***	-0.049***	-0.0031	-0.0033	-0.0039
	(0.011)	(0.011)	(0.011)	(0.0056)	(0.0057)	(0.0059)
Precip. bin 4	-0.11***	-0.11***	-0.11***	-0.0087	-0.0091	-0.0094
	(0.014)	(0.014)	(0.014)	(0.0058)	(0.0058)	(0.0061)
Precip. bin 5	-0.15***	-0.15***	-0.16***	-0.030***	-0.030***	-0.031***
	(0.024)	(0.023)	(0.024)	(0.011)	(0.011)	(0.011)
Year*Month FE	X	X	X	X	X	X
Day of Week FE	X	X	X	X	X	X
First Stage F-Stat		30.6	28.1		30.6	28.1
Observations	3351	3351	3117	3351	3351	3117
R-Squared	0.75	0.75	0.76	0.78	0.78	0.78

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered on the month of sample. Dependent variable is the daily citywide crime count. Regression also includes first-of-month and first-of-year dummies. Excluded instruments are 20 degree bins for daily average wind direction at Midway Airport, and a measure of the net daily average wind power. PM is the mean over monitors 31-22-3 and 31-1016-3.

Table 4: Violent crime downwind of interstates

	(1)	(2)	(3)	(4)
Treatment (downwind)	0.0694***	0.0231**	0.0231**	0.0234**
	(0.0134)	(0.0117)	(0.0110)	(0.0113)
Route*Side FE		X	X	X
Route*Date FE			X	X
Route*Side Weather Interact.				X
Observations	41730	41730	41730	41730
R-Squared	0.000644	0.274	0.678	0.680

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.

Table 5: Property crime downwind of interstates

	(1)	(2)	(3)	(4)
Treatment (downwind)	0.0108	-0.0101	-0.0101	-0.00457
	(0.0509)	(0.0326)	(0.0295)	(0.0304)
Route*Side FE		X	X	X
Route*Date FE			X	X
Route*Side Weather Interact.				X
Observations	41730	41730	41730	41730
R-Squared	0.00000107	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. 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 6: Violent crime downwind of interstates, by specific crime

	(1)	(2)	(3)	(4)
Treatment (downwind)	0.00227	0.00309	-0.0119*	0.0300***
	(0.00185)	(0.00293)	(0.00610)	(0.00861)
Crime Type	Homicide	Rape	Agg. Assault	Agg. Battery
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	41730	41730	41730	41730
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.

Table 7: Property crime downwind of interstates, by specific crime

	(1)	(2)	(3)	(4)	(5)
Treatment (downwind)	0.00482	-0.00358	-0.00799	0.00298	-0.000807
	(0.0100)	(0.0125)	(0.0221)	(0.0115)	(0.00191)
Crime Type	Robbery	Burglary	Larceny	Gr. Theft Auto	Arson
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	41730	41730	41730	41730	41730
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.

Table 8: Downwind violent crime, by season

	(1)	(2)	(3)	(4)
Treatment (downwind)	0.0953***	-0.0305	-0.0305	0.00225
	(0.0218)	(0.0204)	(0.0192)	(0.0206)
Treatment*Spring	-0.0521	0.0981***	0.0981***	0.0528*
	(0.0349)	(0.0311)	(0.0294)	(0.0302)
Treatment*Summer	-0.0252	0.0783**	0.0783**	0.0296
	(0.0369)	(0.0321)	(0.0304)	(0.0318)
Treatment*Autumn	-0.0261	0.0303	0.0303	-0.00344
	(0.0342)	(0.0299)	(0.0283)	(0.0290)
Main Effects	X	X		
Route*Side FE		X	X	X
Route*Date FE			X	X
Route*Side Weather Interact.				X
Observations	41730	41730	41730	41730
R-Squared	0.0216	0.290	0.678	0.680

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

Table 9: Downwind violent crime, by weekday/weekend

	(1)	(2)	(3)	(4)
Treatment (downwind)	0.0839***	0.0363	0.0363*	0.0378*
	(0.0268)	(0.0232)	(0.0220)	(0.0221)
Treatment*Weekday	-0.0201	-0.0185	-0.0185	-0.0200
	(0.0309)	(0.0265)	(0.0251)	(0.0250)
Main Effects	X	X		
Route*Side FE		X	X	X
Route*Date FE			X	X
Route*Side Weather Interact.				X
Observations	41730	41730	41730	41730
R-Squared	0.00485	0.278	0.678	0.680

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.

Table 10: Downwind violent crime, by wind bins

	(1)	(2)	(3)	(4)
Treatment*(Wind speed 0 - 2 m/s)	-0.0211	-0.0168	-0.00367	0.00959
	(0.0458)	(0.0409)	(0.0587)	(0.0587)
Treatment*(Wind speed 2 - 4 m/s)	0.101***	0.0673***	0.0341**	0.0358**
	(0.0181)	(0.0155)	(0.0174)	(0.0174)
Treatment*(Wind speed 4 - 6 m/s)	0.0885***	0.0262*	0.0150	0.0135
	(0.0181)	(0.0157)	(0.0172)	(0.0175)
Treatment*(Wind speed 6 - 8 m/s)	-0.0290	-0.0817***	0.0132	0.0113
	(0.0279)	(0.0240)	(0.0292)	(0.0294)
Treatment*(Wind speed 8 - 10 m/s)	-0.101*	-0.155***	0.0441	0.0382
	(0.0542)	(0.0458)	(0.0596)	(0.0596)
Treatment*(Wind speed 10 - 12 m/s)	0.0171	-0.155	0.121	0.109
	(0.193)	(0.156)	(0.171)	(0.169)
Route*Side FE		X	X	X
Route*Date FE			X	X
Route*Side Weather Interact.				X
Observations	41730	41730	41730	41730
R-Squared	0.00140	0.274	0.678	0.680

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.

Table 11: Downwind violent crime, by treatment angle and distance from interstate

	Angle width	30	45	60	75	90
$\frac{1}{4}$ mile						
	Est.	0.0070	0.0112*	0.0137***	0.0100**	0.0090**
	SE	(0.0076)	(0.0060)	(0.0051)	(0.0044)	(0.0040)
	N	20608	31250	41730	51924	61362
	R^2	0.578	0.582	0.588	0.587	0.588
$\frac{1}{2}$ mile						
	Est.	0.0152	0.0168*	0.0160**	0.0154**	0.0164***
	SE	(0.0117)	(0.0092)	(0.0077)	(0.0067)	(0.0061)
	N	20608	31250	41730	51924	61362
	R^2	0.637	0.639	0.642	0.641	0.64
1 mile						
	Est.	0.0252	0.0235*	**0.0234****	0.0166*	0.0152*
	SE	(0.0170)	(0.0134)	**(0.0113)**	(0.0099)	(0.0090)
	N	20608	31250	**41730**	51924	61362
	R^2	0.676	0.678	**0.680**	0.680	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.

Table 12: Downwind violent crime, including lagged variables

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (downwind)	0.0234**	0.0263**	0.0256**	0.0255**	0.0262**	0.0261**
	(0.0113)	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0121)
Downwind, t-1		-0.00491	-0.00272	-0.00260	-0.00352	-0.00296
		(0.00722)	(0.00757)	(0.00757)	(0.00757)	(0.00756)
Downwind, t-2			-0.00667	-0.00720	-0.00686	-0.00719
			(0.00708)	(0.00736)	(0.00736)	(0.00735)
Downwind, t-3				0.00161	0.00172	0.00111
				(0.00709)	(0.00708)	(0.00708)
Number of crimes, t-1					0.0407***	0.0372***
					(0.00846)	(0.00846)
Number of crimes, t-2						0.0357***
						(0.00852)
Number of crimes, t-3						0.0382***
						(0.00868)
Route*Side FE	X	X	X	X	X	X
Route*Date FE	X	X	X	X	X	X
Route*Side Weather Interact.	X	X	X	X	X	X
Observations	41730	41730	41730	41730	41730	41730
R-Squared	0.680	0.680	0.680	0.680	0.681	0.682

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.

Table 13: Downwind violent crime, alternative identification strategy

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (binary)	0.0287**	0.0303**	0.0303**			
	(0.0138)	(0.0150)	(0.0146)			
Treatment (continuous)				0.0175*	0.0187*	0.0187*
				(0.00901)	(0.00987)	(0.00956)
Route*Side*Month FE	X			X		
Route*Side*DoY FE		X	X		X	X
Covariate Interactions			X			X
Observations	61362	61362	61362	61362	61362	61362
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.