Air Pollution and Criminal Activity: Evidence from Chicago Microdata

Evan Herrnstadt [†]
Erich Muehlegger [‡]

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Preliminary and incomplete – Comments welcome

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 ten-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 a three percent increase in violent crime on the downwind side. Interestingly, the effect is unique to violent crimes - we find no effect of pollution on the commission of property crime.

*The authors thank Brian Saville at travelmidwest.com for graciously providing the traffic data.
[†]University of Michigan, eherrnst@umich.edu
[‡]University of California - Davis and NBER. emuehlegger@ucdavis.edu.

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 deleterious 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 documenting the first quasi-experimental evidence that air pollution affects violent criminal activity.

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 over a ten-year period. Our empirical strategy is relatively straightforward. The point source of pollution on which we focus our attention are major interstates that transect the city of Chicago, including I-90, I-94, I-290, I-55 and I-57. Our identification strategy estimates 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. As an example, I-290 runs east 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 falls predominately on the north side of the interstate, whereas when the wind blows from the north, the pollution impacts the south-side 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. In essence, the side of the interstate from which the wind blows acts allows us to control for variation in day-to-day 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 approximately three percent on the downwind side. Interestingly, the effects we find are unique to violent crimes - we find no effect of pollution on the commission of property crime. We find that the effect of being downwind is attenuated on days when the direction of the wind is not orthogonal to the road.

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

Furthermore, we find relatively strong evidence that source of the deleterious pollution are mobile sources traveling on interstates. As a falsification test, we consider alternative "roads" parallel to I-290 and find that the downwind estimate is maximized precisely at the latitude that I-290 transects the Chicago. Finally, we present suggestive evidence that the effect on violent crime is driven by carbon monoxide (or other pollutants that manifest in cold weather) rather than NOx. When we allow treatment effect to vary by season, we find that the point estimate of the downwind effect greatest during winter 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 economic literatures focused on the relationship between the prevalence of criminal activity and the surrounding environment.

The largest literature documents a link between temperature and crime. Rotton and Cohn (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, Lefgren, and Moretti (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. Finally, Ranson (2012) 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 violence is generally linear in temperature. Compared to mild days, property crime is lower during cold spells, but not any higher during hot days.

Ambient light is another environmental factor affecting crime. If criminals are more easily detected, then crime would be expected to decrease with light. However, light also might encourage people to stay out later; the number of interactions and, thus, the opportunities for crime, would increase. Doleac and Sanders (2012) exploit variation induced by daylight saving time to estimate the causal effect of light on crime. They find that light reduces robbery,

murder, and rape by approximately 50%, while leaving non-light-dependent crime (such as forgeries) unaffected.

Research examining a possible link between ambient air 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 estimates 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 have a direct physiological effect on the potential criminal.

Why would one expect air pollution to affect cognitive function? Block and Calderón-Garcidueñas (2009) provide a very concise overview of some of the possible pathways. One possible mechanism is the direct entry of ultra-fine particulate matter into the brain itself. Once the particles reach the brain, medical researchers posit two mechanisms for toxicity: the chemical makeup of the particle itself or the triggering of an inflammatory response. Another possible mechanism is that the particles may actually operate as a delivery vehicle for other toxic compounds attached to the surface of the particle. Ozone is a highly reactive substance that reacts with molecules in the body to create toxins and stimulate inflammation.

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.

Because of the ethical concerns involved, lab experiments in which human subjects are exposed to pollution are rare. Thus, Rotton (1983) and Rotton, Barry, Frey, and Soler (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.

Finally, there is some evidence that psychological events are more prevalent on days with higher 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 (Kim, et al (2010); 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, Ebenstein, and Roth (2012) 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 (2013) 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.

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, sexual assault, robbery, assault, battery, burglary, larceny, arson, and grand theft auto. We further separate these crimes into violent crimes (homicide, sexual assault, 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 of the month 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.

As is the case with any crime data, there are a couple issues to consider. First, the crimes available are those reported, 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. That is, it is problematic only if crimes are more or less likely to be reported when pollution is blowing into an area than when it is not. Second, the timing of crimes is reported by whoever is making the report. 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.[5]

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

3.4 Traffic Data

For the latter half of our sample period, we obtained traffic data at 1026 uni-directional expressway traffic monitors operated by the Chicago Department of Transportation and the Illinois DOT, and reported by travelmidwest.com. Every half-hour, each monitor reports average traffic speed and vehicle volume (measured in vehicles per hour per lane) over the most recent five-minute interval.

[5]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.

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, 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 6and 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 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 a similar spirit as Schlenker and Walker (2013), who use wind direction and airport emissions to instrument for ambient pollution in California to estimate causal health effects.

We estimate the following IV/2SLS specification:

$$Poll_t = \alpha W_t + \beta_1 X_t + \epsilon_t \quad (1)$$

$$ln(Crime_t) = \beta_2 X_t + \widehat{Poll}_t + \nu_t \quad (2)$$

W_t includes daily average wind direction in 20-degree bins and the interaction of these bins with average daily wind power. X_t is a vector of controls including 5°C daily maximum temperature bins, 5 total daily precipitation bins, 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 wind power-direction interaction only affect crime directly through the pollution moved in or out of the city.

Wind direction and 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 wind speed in the second stage regression, leaving wind direction as the only plausible source of contamination. Thus, 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 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. 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 regression suggest a causal relationship between 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 locations associated with each crime.

5 The micro-geography of pollution and crime

While the city-level regressions provides suggestive evidence of the relationship between pollution and crime, it is 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, our estimate of the effect of pollution on crime may be biased. Consequently, we may make an incorrect inference about the relationship between pollution and criminal activity.

To provide more convincing evidence of the relationship between crime and pollution, 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, that summarizes CO readings at one of the monitors in our data (31-6004-1). This monitor is located immediately north of I-290, which runs straight 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 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 hard enough to widely disperse air emissions. 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.[6]

Our identification strategy is easiest to explain using I-290 as an example. I-290 runs (essentially) straight west from Chicago. To causally estimate the effect of pollution on crime, we compare crimes along the north-side of I-290 and 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 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

[6]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.

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 O'Hare airport - criminal activity near an airport is unlikely to be representative of criminal activity elsewhere. The southwestern part of the city borders Lake Michigan to the east and Lake Calumet to the southwest, differentially affecting the possibility of criminal activity on sides of I=90 and I-94. Finally, we exclude crimes on the western edges of I-55 and I-290. Westward of longitude -87.74, I-55 exits (and then re-enters) the city and I-290 runs along the city limits.

For our main specification, consider crimes within one mile of either side of the interstate and days on which the wind is blowing within forty-five degrees of the line orthogonal to the direction of the interstate.[7] Thus, for I-290, running east and west, we focus on days for which the wind blows from a direction between 315 degrees (NW) and 45 degrees (NE) or from a direction between 135 degrees (SE) and 225 degrees (SW). We relax both of these assumptions in robustness checks.

Our main specification regresses crime on side s of interstate i on day t on interstate*side FE, interstate*day FE and a dummy variable equal to one if side s is the side downwind from the interstate. Formally,

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

We consider two dependent variables: (1) the total number of crimes, and (2) the total number of crimes as a fraction of the mean. We consider the standardized number of crimes to control for difference in absolute levels of criminal activity in different locations as well as facilitate the comparison of violent crimes and (more-numerous) property crimes. Interstate*side fixed effects (α) control for time invariance 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 control 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.

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

5.1 Main Results

We present the results for violent crime in Tables 4. The top and bottom panels of the table correspond to the two dependent variables: the total number of crimes in the top panel and the standardized total number of crimes in the bottom panel. Column (4) corresponds to the main specification in equation (3), while columns (1) through (3) present the results of specification that replace the interstate*date fixed effects with coarser fixed effects and weather covariates. Focusing the main specification, we find that the downwind side of the interstate experiences 0.0753 more violent crimes per day. When measured relative to the mean number of crimes, this represents an increase of approximately 3.1 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. For the threat to identification above to be valid, stories like the one for I-290 above, 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 (5), we allow for the rate of crime on the each of the fourteen interstate sides to vary with independently with temperature, precipitation and by month-of-year, covariates that are correlated with both crime and pollution. Formally, column (5) 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, precipitation over the course of the day and month-of-year fixed effects. In this specification, we estimate the effect of being downwind of an interstate by comparing crime on the up- and downwind sides after conditioning on temperature, precipitation and month-of-year. We do not find strong evidence that the three most obvious correlates with criminal activity drive our results above - when we allow for criminal activity on the each side of the road to vary independently with temperature, precipitation and month-of-year, we estimate that the downwind side experience 0.0675 more

violent crimes per day, an increase of approximately 2.9 percent.

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 either in absolute or mean-relative terms.

5.2 Robustness checks

Two assumptions underlie our analysis in table 4. First, when constructing the sample, we include any day in which the wind blows within at least 45 degrees of the vector orthogonal to the direction of the road. Second, when counting the number of violent and property 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 6 presents the results of the main specification (equation (3)) as we vary the inclusion rule based on the number of degrees around the orthogonal vector to the direction of the road. For reference, column (3) corresponds to the assumption (45 degrees) used in the main table.

As an illustration, if we consider I-290, running straight east-west, in column (1), we would only include days in our estimation during which the wind blows between 345 degrees and 15 degrees or between 165 degrees and 195 degrees.[8] In contrast, in column (6), we would include all the days in the dataset - any day during which the wind blew in any northernly 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 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 (6). In the case of I-290, if, on a day, the wind blows towards 271 degrees, one degree north of straight 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. With the exception of the increase from 15 degrees to 30 degrees, increasing the inclusion angle attenuates the point estimate of the downwind effect - identically to the way, non-compliance attenuates an intent-to-treat estimate.

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

Table 7 presents estimates in which the size of the band on either side of the interstate varies in quarter-mile increments between one-quarter mile and one mile.[9] The estimates increase approximately linearly with the size of the band, up to one-mile, suggesting that the crime on the downwind side of the interstate increases in a relatively uniform fashion with distance from the interstate.

5.3 Falsification tests

As an additional piece of evidence, we consider a falsification test of our identification strategy. To motivate the falsification test, consider the following thought exercise. Suppose we didn't know at what latitude I-290 cut 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 10 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 11 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 (4) of Table 4, although this exercise only examines one of the seven interstate segments.

Three points in particular stand out in Figure 11. 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

[9] 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.

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, roughly latitude 41.84) is at the northern end of the I-55 as it exits the sample region of the falsification test.

5.4 Specific pollutants and criminal activity

Finally, it is important to note that we identify the effect of being downwind of an interstate on violent crime, but cannot definitely distinguish between the effect of CO emissions, NOx 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 not definitive, 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, NOx emissions from vehicles tend to be greatest during summer months - NOx emission from mobile sources form at extremely high combustion temperatures, most commonly when engines operating at high temperatures or unable to sufficiently cool.

As indirect evidence of the impact of specific pollutants, we allow for the treatment effect in columns (4) and (5) in table 4 to vary by season. We report the coefficient for the season-specific treatment effects in table 8. Columns (1) and (2) of the table report regressions using the number of crimes as the dependent variable, while columns (3) and (4) report regressions using the standardized number of crimes as the dependent variable, where we standardize by the *season-specific* mean number of daily violent crimes. Across the four specifications, the effect of being downwind of the interstate has the greatest impact on violent crime during winter months. Relative the three percent increase in violent crimes observed over the entire year, being the downwind side of the interstate is associated with a seven percent increase in violent crime in the winter. In contrast, the season-specific treatment effects are not statistically distinguishable from zero in the spring and summer months in all but the first specification. Although not

dispositive, the seasonal treatment effects provide suggestive evidence that carbon monoxide (or other winter-specific mobile emissions) as the primary channel by which violent activity increases rather than NOx emissions.

6 Conclusion

In this paper, we provide the first quasi-experimental evidence that air pollution affects violent criminal activity. We estimate that the downwind side of interstates experience three 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, the annual aggregate costs of crime are significant. Although 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 a trillion dollars annually.

7 Figures

Figure 1: Crime share by hour of day

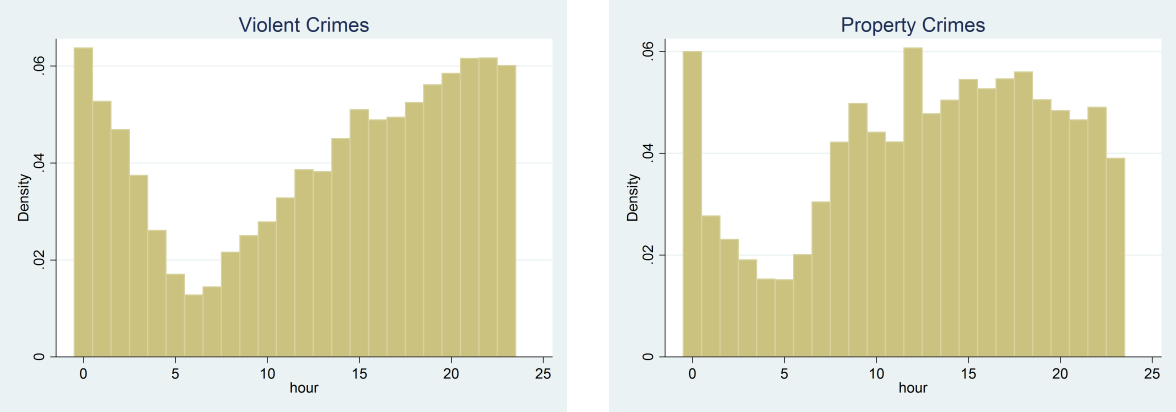


Figure 2: Average crimes by week of year

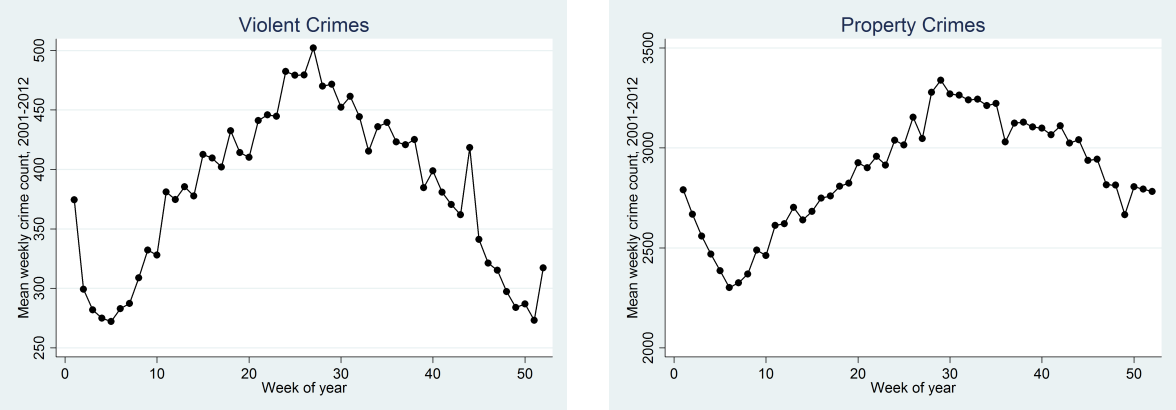


Figure 3: Normalized average annual crimes (2001 levels = 100)

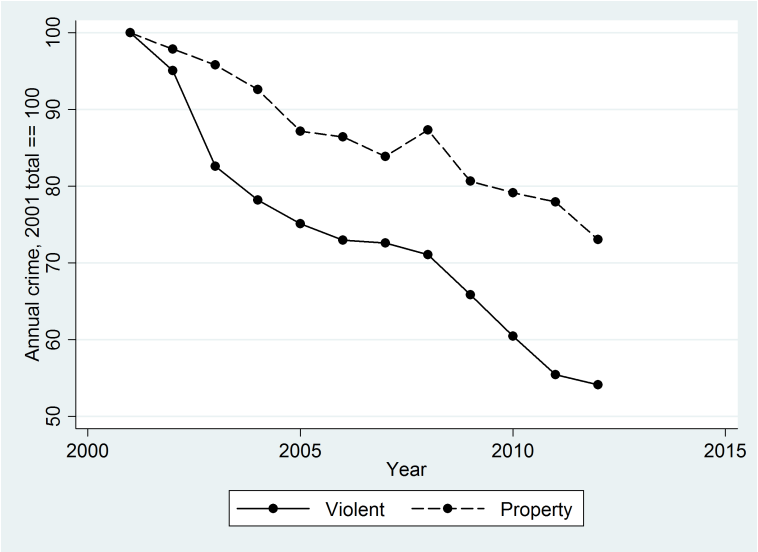


Figure 4: Crime density heat maps

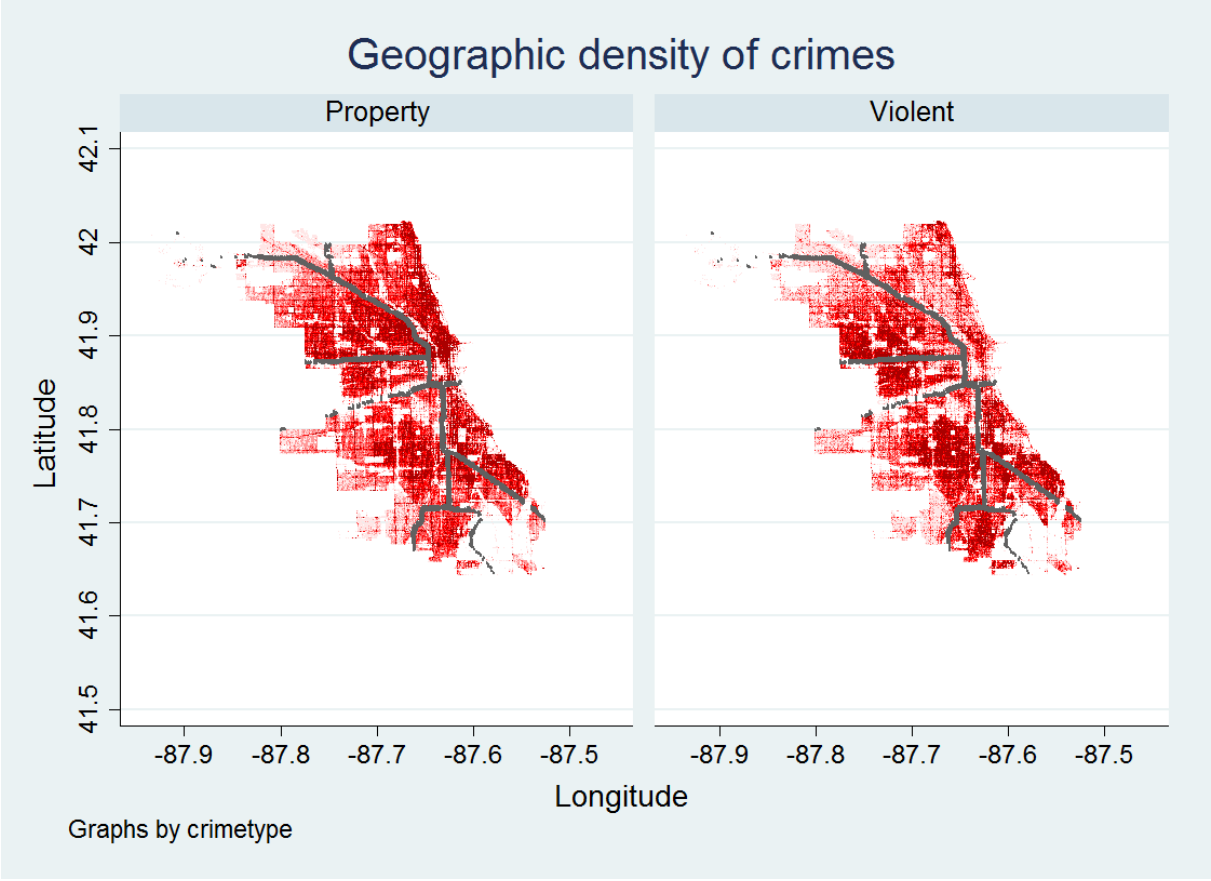


Figure 5: Seasonality in CO and PM_{10} emissions

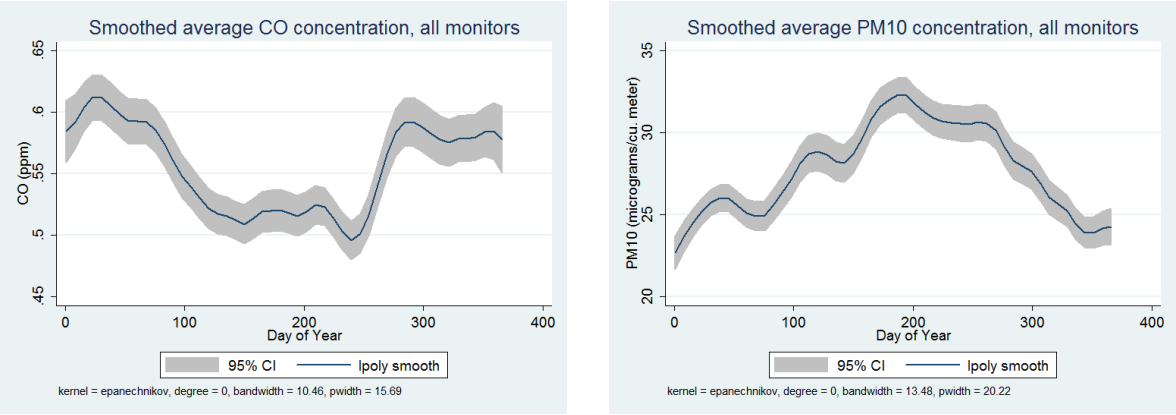


Figure 6: Average PM10 reading as a function of wind direction and speed

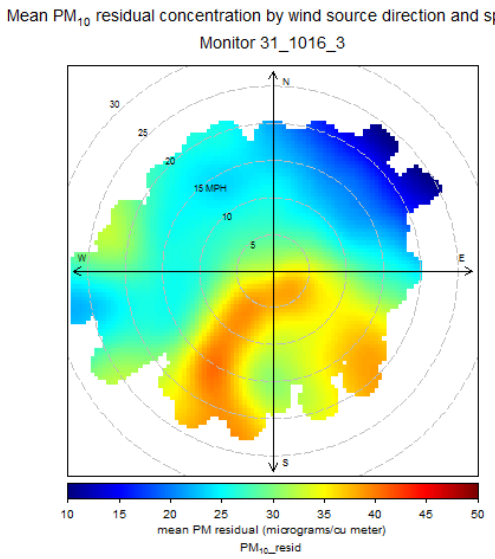


Figure 7: Average CO reading as a function of wind direction and speed

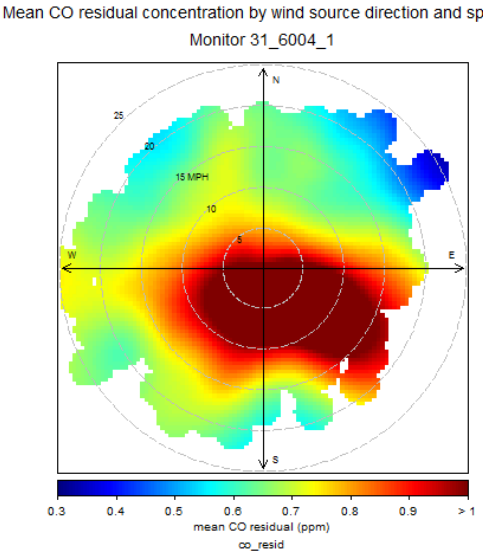


Figure 8: Sample set for interstate identification strategy

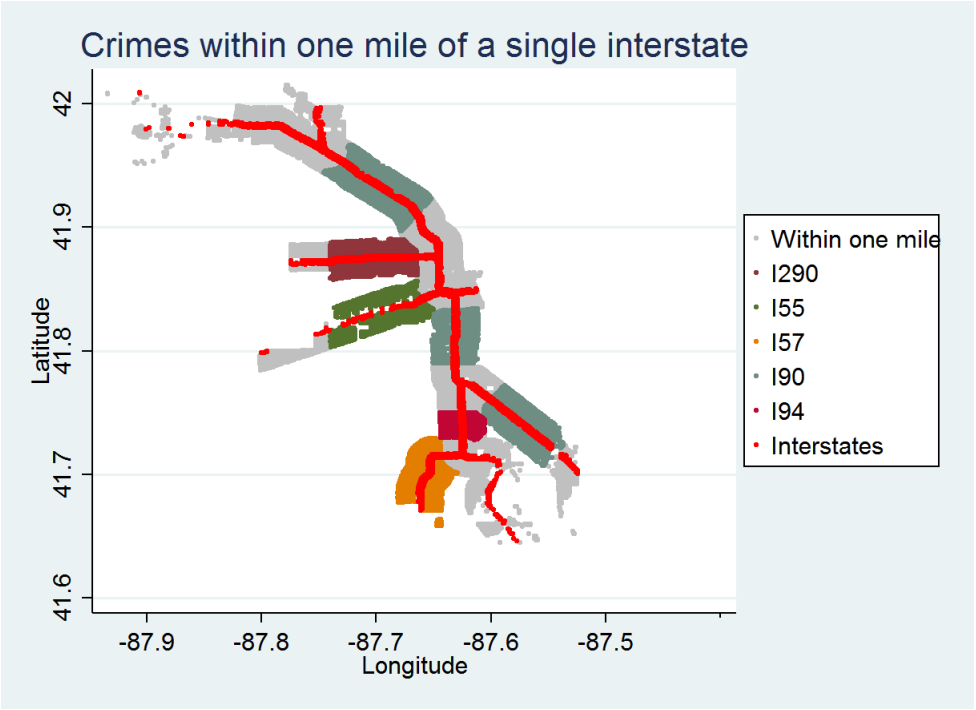
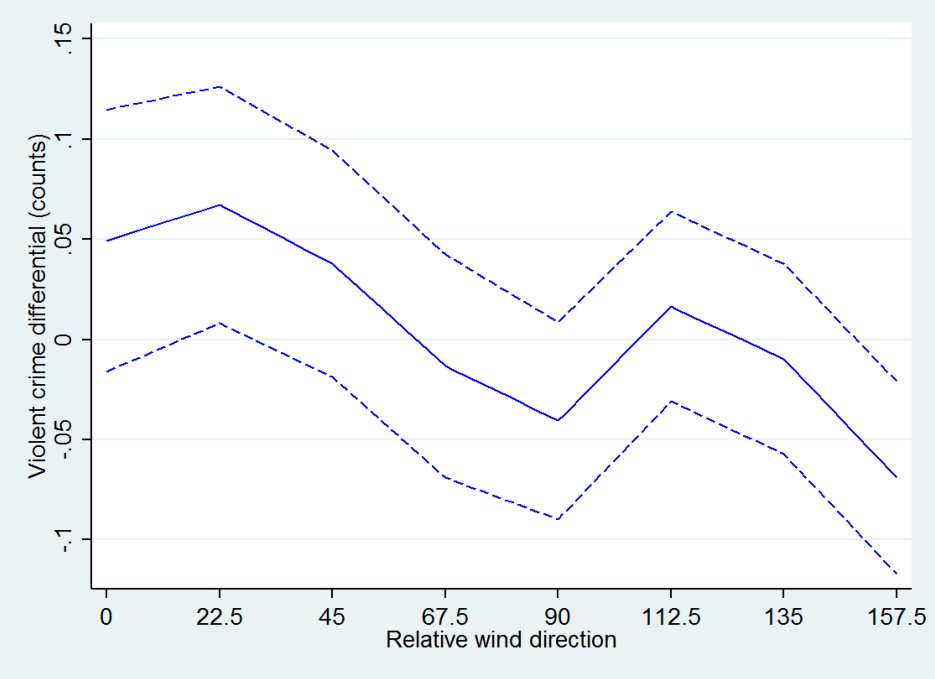


Figure 9: Difference in violent crime, by relative wind vector



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: Sample set for interstate identification strategy

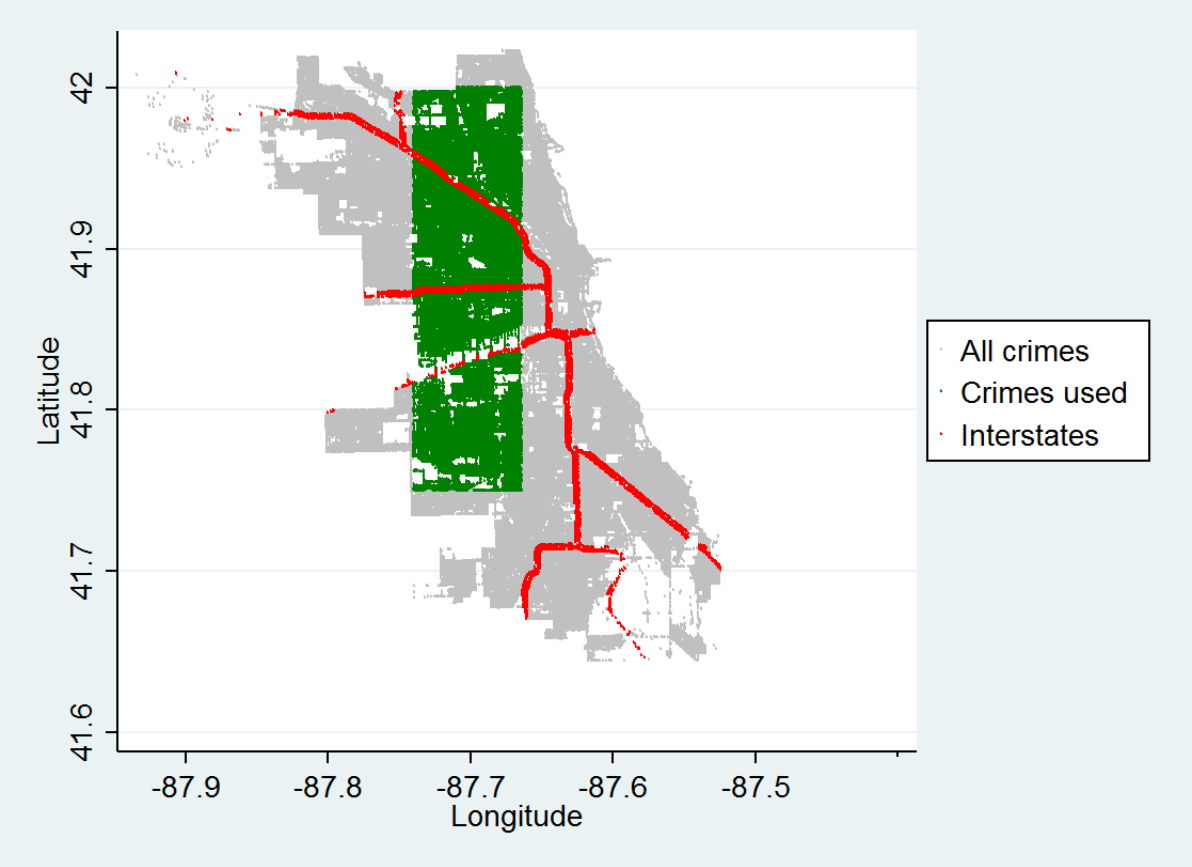
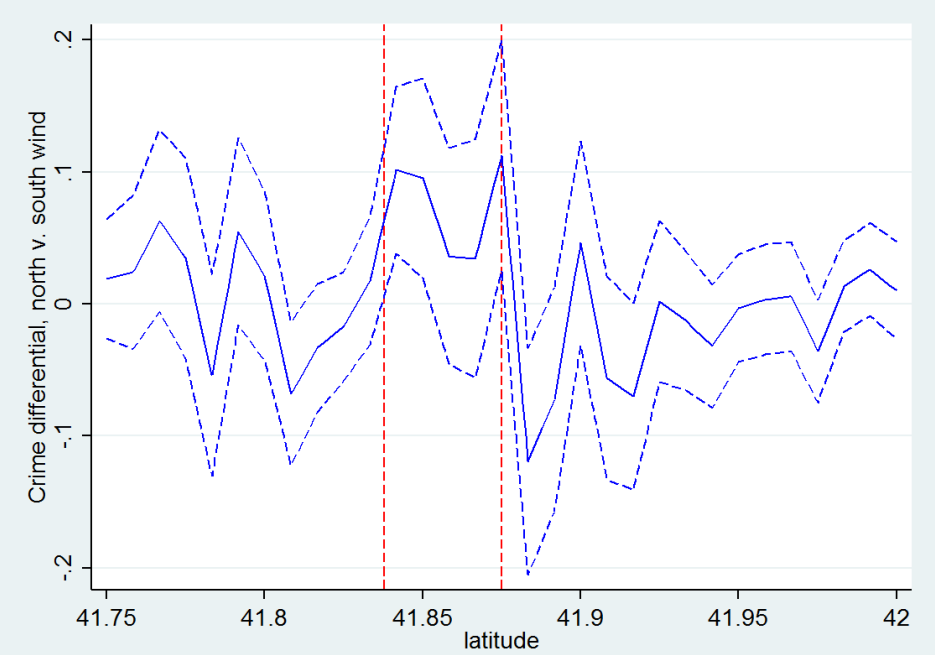


Figure 11: North-south crime differential, alternative latitudes



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 45 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

VARIABLES	(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_avg_co	-0.0160	0.0938**	0.111**	0.0110	0.0104	0.00934
	(0.0230)	(0.0450)	(0.0467)	(0.0106)	(0.0200)	(0.0203)
speed_norm	-0.000550**	-1.52e-05	6.72e-05	7.26e-05	6.95e-05	4.66e-05
	(0.000231)	(0.000293)	(0.000309)	(8.99e-05)	(0.000126)	(0.000127)
_IMidwayMax_2	0.0849***	0.0838***	0.0832***	0.0561***	0.0561***	0.0561***
	(0.0238)	(0.0236)	(0.0268)	(0.0117)	(0.0115)	(0.0133)
_IMidwayMax_3	0.184***	0.181***	0.179***	0.102***	0.102***	0.103***
	(0.0268)	(0.0265)	(0.0289)	(0.0146)	(0.0143)	(0.0161)
_IMidwayMax_4	0.254***	0.248***	0.249***	0.130***	0.130***	0.131***
	(0.0249)	(0.0245)	(0.0270)	(0.0164)	(0.0160)	(0.0181)
_IMidwayMax_5	0.345***	0.338***	0.337***	0.157***	0.157***	0.159***
	(0.0267)	(0.0262)	(0.0286)	(0.0166)	(0.0162)	(0.0183)
_IMidwayMax_6	0.431***	0.423***	0.424***	0.165***	0.165***	0.166***
	(0.0274)	(0.0268)	(0.0294)	(0.0162)	(0.0159)	(0.0178)
_IMidwayMax_7	0.540***	0.528***	0.527***	0.165***	0.165***	0.165***
	(0.0287)	(0.0281)	(0.0310)	(0.0168)	(0.0165)	(0.0185)
_IMidwayMax_8	0.622***	0.607***	0.607***	0.167***	0.167***	0.167***
	(0.0297)	(0.0293)	(0.0319)	(0.0171)	(0.0169)	(0.0190)
_IMidwayMax_9	0.692***	0.673***	0.677***	0.173***	0.173***	0.176***
	(0.0305)	(0.0302)	(0.0329)	(0.0178)	(0.0176)	(0.0197)
_IMidwayMax_10	0.686***	0.660***	0.657***	0.198***	0.198***	0.184***
	(0.0436)	(0.0433)	(0.0500)	(0.0226)	(0.0226)	(0.0232)
_IMidwayPre_1	-0.0236***	-0.0217***	-0.0218***	-0.000466	-0.000477	-0.000520
	(0.00801)	(0.00788)	(0.00840)	(0.00429)	(0.00416)	(0.00447)
_IMidwayPre_2	-0.0641***	-0.0618***	-0.0615***	-0.00448	-0.00449	-0.00511
	(0.0104)	(0.0103)	(0.0113)	(0.00522)	(0.00522)	(0.00536)
_IMidwayPre_3	-0.124***	-0.121***	-0.126***	-0.0101	-0.0101*	-0.0122*
	(0.0145)	(0.0143)	(0.0146)	(0.00621)	(0.00605)	(0.00654)
_IMidwayPre_4	-0.149***	-0.145***	-0.153***	-0.0290***	-0.0290***	-0.0278**
	(0.0248)	(0.0243)	(0.0244)	(0.0105)	(0.0103)	(0.0111)
month1	0.169***	0.169***	0.167***	0.183***	0.183***	0.184***
	(0.0150)	(0.0148)	(0.0153)	(0.00677)	(0.00660)	(0.00674)
jan1	1.055***	1.059***	1.047***	0.294***	0.294***	0.276***
	(0.0455)	(0.0451)	(0.0505)	(0.0484)	(0.0472)	(0.0505)
Constant	4.027***	3.899***	3.875***	5.827***	5.827***	5.830***
	(0.0370)	(0.0591)	(0.0617)	(0.0154)	(0.0241)	(0.0246)
Observations	3,467	3,467	3,231	3,467	3,467	3,231
R-squared	0.749	0.747	0.748	0.778	0.778	0.777
Day of week FE	X	X	X	X	X	X
Year-Month FE	X	X	X	X	X	X
F-Stat	.	19.03	18.76	.	19.03	18.76

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. 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

VARIABLES	(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_avgpm10	0.000899***	0.00116*	0.00134*	5.09e-05	-1.88e-05	6.04e-05
	(0.000314)	(0.000658)	(0.000686)	(0.000158)	(0.000301)	(0.000309)
speed_norm	-0.000345*	-0.000323	-0.000327	1.09e-05	5.03e-06	-1.26e-06
	(0.000200)	(0.000205)	(0.000216)	(8.93e-05)	(9.03e-05)	(9.24e-05)
_IMidwayMax_2	0.112***	0.113***	0.113***	0.0571***	0.0569***	0.0588***
	(0.0250)	(0.0245)	(0.0263)	(0.0127)	(0.0123)	(0.0135)
_IMidwayMax_3	0.208***	0.209***	0.209***	0.103***	0.103***	0.105***
	(0.0292)	(0.0289)	(0.0300)	(0.0165)	(0.0159)	(0.0180)
_IMidwayMax_4	0.275***	0.276***	0.277***	0.134***	0.133***	0.135***
	(0.0265)	(0.0259)	(0.0269)	(0.0179)	(0.0174)	(0.0200)
_IMidwayMax_5	0.359***	0.358***	0.357***	0.157***	0.157***	0.159***
	(0.0274)	(0.0267)	(0.0279)	(0.0182)	(0.0178)	(0.0204)
_IMidwayMax_6	0.441***	0.439***	0.438***	0.165***	0.166***	0.167***
	(0.0284)	(0.0280)	(0.0296)	(0.0179)	(0.0180)	(0.0206)
_IMidwayMax_7	0.542***	0.538***	0.536***	0.165***	0.166***	0.166***
	(0.0297)	(0.0303)	(0.0324)	(0.0187)	(0.0197)	(0.0223)
_IMidwayMax_8	0.613***	0.606***	0.602***	0.169***	0.171***	0.168***
	(0.0311)	(0.0342)	(0.0363)	(0.0194)	(0.0213)	(0.0242)
_IMidwayMax_9	0.672***	0.662***	0.658***	0.176***	0.179***	0.179***
	(0.0336)	(0.0398)	(0.0429)	(0.0209)	(0.0244)	(0.0276)
_IMidwayMax_10	0.659***	0.645***	0.638***	0.205***	0.209***	0.193***
	(0.0462)	(0.0543)	(0.0613)	(0.0248)	(0.0307)	(0.0317)
_IMidwayPre_1	-0.0157*	-0.0151*	-0.0155*	-0.000158	-0.000317	-0.000584
	(0.00852)	(0.00821)	(0.00873)	(0.00437)	(0.00421)	(0.00454)
_IMidwayPre_2	-0.0521***	-0.0512***	-0.0491***	-0.00311	-0.00334	-0.00388
	(0.0106)	(0.0106)	(0.0115)	(0.00559)	(0.00571)	(0.00588)
_IMidwayPre_3	-0.111***	-0.109***	-0.113***	-0.00868	-0.00907	-0.00943
	(0.0143)	(0.0143)	(0.0141)	(0.00580)	(0.00580)	(0.00609)
_IMidwayPre_4	-0.151***	-0.149***	-0.160***	-0.0296***	-0.0301***	-0.0309***
	(0.0236)	(0.0234)	(0.0240)	(0.0109)	(0.0108)	(0.0113)
month1	0.163***	0.163***	0.160***	0.179***	0.180***	0.181***
	(0.0152)	(0.0149)	(0.0155)	(0.00685)	(0.00666)	(0.00679)
jan1	1.071***	1.072***	1.062***	0.294***	0.294***	0.274***
	(0.0419)	(0.0405)	(0.0435)	(0.0490)	(0.0479)	(0.0507)
Constant	3.940***	3.932***	3.927***	5.832***	5.834***	5.830***
	(0.0277)	(0.0331)	(0.0345)	(0.0152)	(0.0150)	(0.0165)
Observations	3,351	3,351	3,117	3,351	3,351	3,117
R-squared	0.754	0.753	0.756	0.780	0.780	0.779
Day of week FE	X	X	X	X	X	X
Year-Month FE	X	X	X	X	X	X
F-Stat	.	30.62	28.06	.	30.62	28.06

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. PM is the mean over monitors 31-22-3 and 31-1016-3.

Table 4: Violent crime downwind of interstates

	(1)	(2)	(3)	(4)	(5)
Downwind	0.0902***	0.0901***	0.0863***	0.0753***	0.0675***
	(0.0164)	(0.0164)	(0.0165)	(0.0174)	(0.0184)
Max. Temp	linear	binned			
Wind Speed	X	X			
Month*Year FE	X	X			
Date FE			X		
Route*Date FE				X	X
Route*Side Covar. Interact.					X
Observations	23838	23838	23838	23838	23838
R-Squared	0.207	0.207	0.339	0.555	0.558

	(1)	(2)	(3)	(4)	(5)
Downwind	0.0373***	0.0372***	0.0358***	0.0313**	0.0285**
	(0.0113)	(0.0113)	(0.0116)	(0.0127)	(0.0138)
Max. Temp	linear	binned			
Wind Speed	X	X			
Month*Year FE	X	X			
Date FE			X		
Route*Date FE				X	X
Route*Side Covar. Interact.					X
Observations	23838	23838	23838	23838	23838
R-Squared	0.0551	0.0554	0.184	0.415	0.418

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors reported. All specifications include interstate*side fixed effects. The dependent variable in the top (bottom) panel is the number of crimes (standardized 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 45 degrees of the vector orthogonal to the direction of the interstate.

Table 5: Property crime downwind of interstates

	(1)	(2)	(3)	(4)	(5)
Downwind	-0.0505	-0.0504	-0.0516	-0.0520	-0.0327
	(0.0366)	(0.0366)	(0.0359)	(0.0348)	(0.0381)
Max. Temp	linear	binned			
Wind Speed	X	X			
Month*Year FE	X	X			
Date FE			X		
Route*Date FE				X	X
Route*Side Covar. Interact.					X
Observations	31190	31190	31190	31190	31190
R-Squared	0.643	0.644	0.705	0.839	0.842

	(1)	(2)	(3)	(4)	(5)
Downwind	-0.00748	-0.00746	-0.00740	-0.00622	-0.00607
	(0.00544)	(0.00543)	(0.00534)	(0.00529)	(0.00601)
Max. Temp	linear	binned			
Wind Speed	X	X			
Month*Year FE	X	X			
Date FE			X		
Route*Date FE				X	X
Route*Side Covar. Interact.					X
Observations	31190	31190	31190	31190	31190
R-Squared	0.0784	0.0800	0.229	0.563	0.565

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors reported. All specifications include interstate*side fixed effects. The dependent variable in the top (bottom) panel is the number of crimes (standardized 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 45 degrees of the vector orthogonal to the direction of the interstate.

Table 6: Downwind violent crime, by treatment angle

	(1)	(2)	(3)	(4)	(5)	(6)
	15 deg.	30 deg.	45 deg.	60 deg.	75 deg.	90 deg.
Downwind	0.0837***	0.0876***	0.0753***	0.0689***	0.0559***	0.0521***
	(0.0312)	(0.0215)	(0.0174)	(0.0150)	(0.0133)	(0.0122)
Observations	7662	15844	23838	31696	39290	46312
R-Squared	0.549	0.553	0.555	0.558	0.557	0.557

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 an interstate as a fraction of the mean, on one side of the interstate. All specifications include interstate*side fixed effects and interstate*date fixed effects.

Table 7: Downwind violent crime, by distance from interstate

	(1) 1/4 mile	(2) 1/2 mile	(3) 3/4 mile	(4) 1 mile
Downwind	0.0224***	0.0486***	0.0568***	0.0753***
	(0.00744)	(0.0115)	(0.0148)	(0.0174)
Observations	23838	23838	23838	23838
R-Squared	0.553	0.578	0.574	0.555

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 an interstate as a fraction of the mean, on one side of the interstate. All specifications include interstate*side fixed effects and interstate*date fixed effects.

Table 8: Downwind violent crime, by season

	(1)	(2)	(3)	(4)
Treatment * Winter	0.102***	0.124***	0.0678**	0.0700**
	(0.0327)	(0.0346)	(0.0291)	(0.0312)
Treatment * Spring	0.0560	0.0316	0.0264	0.0139
	(0.0348)	(0.0359)	(0.0244)	(0.0256)
Treatment * Summer	0.0706**	0.0513	0.0220	0.0163
	(0.0357)	(0.0365)	(0.0228)	(0.0235)
Treatment * Fall	0.0774**	0.0720**	0.0419*	0.0369
	(0.0344)	(0.0357)	(0.0255)	(0.0267)
Route*Date FE	X	X	X	X
Route*Side Covar. Interact.		X		X
Observations	23838	23838	23838	23838
R-Squared	0.555	0.558	0.401	0.404

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 an interstate as a fraction of the mean, on one side of the interstate. All specifications include interstate*side fixed effects and interstate*date fixed effects.Columns (1) and (2) use the number of crimes as the dependent variable while columns (3) and (4) use the number of crimes as a fraction of mean crimes as the dependent variable.