Air Pollution as a Cause of Violent Crime: Evidence from Los Angeles and Chicago [*]

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Abstract

Exposure to air pollution adversely impacts human health, workplace productivity, educational and a variety of behavioral outcomes. Motivated by research from other disciplines linking pollution to aggression, we provide the first evidence of a causal link between short-run variation in ambient pollution and the commission of violent crime. Using the geolocation of crimes and wind direction as a source of pollution variation, we find air pollution increases violent crime in both Chicago and Los Angeles. We find no effect on property crime. The results suggest that pollution may reduce welfare and affect behavior through an even wider set of channels than previously understood. JEL Codes: Q50 - Q53.

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1 Introduction

Air pollution damages human well-being in a number of ways. A large body of research has quantified a range of adverse effects on adult and infant health.[1] More recent work points to a much wider set of negative impacts, linking variation in air quality to reduced workplace productivity and/or diminished labor market participation[2], compromised cognition and test scores[3] and costly avoidance behavior[4]. In this paper we push the boundary of how far air pollution can influence human behavior and social outcomes still further by providing robust quasi-experimental evidence of a positive causal link from ambient air pollution to same-day violent criminal activity in Chicago and Los Angeles.

Our identification strategy exploits variation in pollution driven by daily changes in wind direction. Wind transports air pollution through urban and suburban environments. Depending on the direction from which the wind is blowing, neighborhoods experience differential changes in air quality conditions. Using detailed information about where crime occurs and controlling for a rich set of weather variables, we compare levels of crime in locations that experience wind-driven surges in pollution with those that don't.

We examine the relationship between crime and pollution in the second and third most populous cities in the United States: Los Angeles (and environs) and Chicago. In Los Angeles, ocean winds blowing on-shore push pollution from downtown Los Angeles to the northeast, into the foothills of the San Gabriel mountains. The San Gabriel mountains trap the pollution, elevating ambient pollution levels in communities in the foothills (such as Pasadena, Burbank and Glendora), except where there is a break between mountain ranges (such as at Santa Clarita). To establish a causal relationship between pollution and crime, we compare crime in communities like Pasadena with those in other parts of the Los Angeles metro area on days with and without winds blowing from the sea. Consistent with evidence from other disciplines on air pollution and aggressive behavior we find that, after controlling for a rich set of additional weather covariates, violent crime increases in locations treated with wind-driven pollution. On treated days (where treatment means a west-wind day in an area where west-wind is associated with dirtier air) violent crime is 6.1 percent higher than on untreated days, relative to control neighborhoods.

We replicate the spirit of the identification strategy in Chicago, but focus on major inter-

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[1] These include Schlenker and Walker (2016), Currie and Walker (2011), Beatty and Shimshack (2014).

[2] Hanna and Oliva (2015), Zivin and Neidell (2012)

[3] Lavy et al. (2014)

[4] Ito and Zhang (2016), Moretti and Neidell (2011), Zivin and Neidell (2009)

states that transect the city of Chicago (the I-90, I-94, I-290, I-55 and I-57), and generate substantial local air pollution. Exploiting the exact geolocation of the two million crimes reported to the Chicago police from 2001 - 2012, 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 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. These effects are unique to violent crimes – consistent with expectations, we find no effect of pollution on property crime.

In each setting we report the results of a battery of robustness and falsification tests, all of which generate favorable results.

Although in each case changes in wind direction are exploited as a quasi-experimental source of variation in air quality, the strategies for causal identification differ, as do the potential threats. Taken together, the robust and congruent results across locations and identification strategies are more persuasive than either individual analysis would be alone. In Los Angeles, we use unique local topography to estimate the effect from within-day variation in pollution in crime across the entire metro area; in Chicago, we focus at a much more local level by isolating sides of major highways. In the case of Los Angeles, the pollution is generated by many sources (both mobile and stationary). In contrast, in Chicago, for each treated side of the interstate, we can use the opposite side of the same interstate as a control, for which economic activity, weather and other correlates of criminal activity are virtually identical and unlikely to be spuriously correlated with seasonal fluctuations in wind direction.

Our paper has clear implications for policy. Crime is a major social concern and the effect sizes that we uncover are substantial. Properly accounting for the impacts of pollution on criminal behavior would increase our estimates of marginal damages, thus increasing the optimal stringency of externality-correcting regulations or Pigouvian pollution taxes. At a broader level the analysis teases further at the nexus between the economy, society and natural environment, widening the set of economic and social outcomes that can plausibly be linked to prevailing environmental conditions. A clean city could be not just a healthy and economically productive city, but also a less violent one.

The rest of the paper proceeds as follows. In Section 2 we summarize the existing literature in biology, medicine and psychology linking air pollution to aggressive behavior. Although ours is the first paper to document a causal effect of air pollution on violent crime, previous research highlights several possible channels that – individually or in combination – might underpin the patterns that we see in the data. Section 3 summarizes data sources. In this section, we also present some cross-sectional/panel regression results that suggest a positive association between ambient air pollution levels and same-day violent crime. Acknowledging the problems with drawing conclusions about causality from this analysis we turn to the central quasi-experimental elements of the paper in Sections 4 (Overview), 5 (Los Angeles) and 6 (Chicago). Section 7 and 8 bring the results together and probe policy implications.

2 Pollution and Violence

This paper is the first, to our knowledge, to document the causal relationship between air pollution and the commission of violent crime.[5] We remain agnostic on the underlying mechanism (or mechanisms). However, it is useful at this stage to note that there is research in medicine, biology and psychology linking pollution exposure to aggression.

The first, and perhaps most straightforward pathway, is that pollution might trigger a psychological response as a result of physical discomfort associated with air pollution exposure.[6] A long literature in psychology summarized by (Anderson and Bushman, 2002) documents a link between physical discomfort and aggressive behavior. Most relevant to our work, Rotton (1983) and Rotton et al. (1978) found laboratory exposure to malodorous reduced subject cognitive performance, tolerance for frustration, and the subjects' ratings of other people and the

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[5] A distinct literature links long-term exposure to lead with violent crime. Using annual state level crime data for Columbia from 1985 to 2002, Reyes (2007) estimates the elasticity of violent crime with respect to childhood lead exposure to be about 0.8. Stretesky and Lynch (2004) exploit spatial variation in lead exposure across 2,772 US counties to establish a similar link, with the greatest effect in the poorest areas. Nevin (2007) finds a strong, robust correlation between violent crime and preschool lead exposure in a panel of high-income countries.

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

physical environment.[7]

A second documented pathway linking pollution and aggression is that air pollution may directly affect brain chemistry. Serotonin (5-Hydroxytrlptamine or 5-HT) is a primary neurotransmitter, responsible for the flow of information in the brain and nervous system. Krueger et al. (1963) was the first study to identify short-term variations in air quality as an important cause of fluctuations in serotonin in the bloodstream. In more recent work, Paz and Huitrón-Reséndiz (1996), González-Guevara et al. (2014) and Murphy et al. (2013) provide experimental evidence linking short-term ozone exposure to decreased serotonin in the brains of animals.[8]

Serotonin is an inhibitor, low levels of which are associated with increased aggression in humans and animals, in both observational and experimental settings (Coccaro et al., 2011). Decreased serotonin is associated with an increased tendency to fight amongst rhesus monkeys (Faustman et al., 1993) and increased impulsive aggression in children (Frankle et al., 2005). In a recent study that involved manipulating the serotonin levels of human subjects within a social experimental setting, Crockett et al. (2013) found that "serotonin-depleted participants were more likely to punish those who treated them unfairly, and were slower to accept fair exchanges". In their summary of the human subject literature, Siegel and Crockett (2013) note that "...a meta-analysis encompassing 175 independent samples and over 6,500 total participants reveals a reliable inverse relationship between serotonin and aggression". Given that criminal assault requires both an attacker and a victim, it is also worth noting that serotonin levels are positively correlated with harm-avoidance behavior in humans (Hansenne et al., 1999); in other words, a serotonin-depleted individual is less likely to flee from an aggressor.

Third, exposure to common air pollutants also leads to oxidative stress and the inflammation of nerve tissues in the body and the brain (neuro-inflammation); "(c)onsistent with findings from human populations, animal studies in dogs, mice and rats show that short-run exposure to air pollution leads to an immediate increase in neuro-inflammation" (Levesque et al., 2011; Van Berlo et al., 2010). Neuro-inflammation is linked to aggressive behavior in animals in experimental settings – Rammal et al. (2008) finds that oxidative stress and inflammation reduces the time to attack and increases the frequency of attack of residential mice

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[7] Similar results have been demonstrated when subjects are exposed to uncomfortable temperatures (Baron and Bell, 1976), noise (Donnerstein and Wilson, 1976) and other physical discomforts. The link between temperature and crime is also well-documented (Ranson, 2014).

[8] Other neurotransmitters have also been implicated, but the mechanisms are poorly understood. For example Kinawy (2009) finds that rats exposed to the fumes of unleaded or leaded gasoline were more aggressive (adopted more aggressive postures, attacked others sooner and more frequently) than a control group exposed to clean air. Subsequent inspection of the brains showed variation in the levels not just of serotonin but other monoamine neurotransmitters such as dopamine and norepinephrine.

towards intruding mice inserted into their "space."

Finally, pollution may lead to other physiological changes that manifest in increased aggression. For example, Maney and Goodson (2011) surveys the literature on the role played by *hormonal* mechanisms in animal aggression. Uboh et al. (2007), for example, provides experimental evidence causally-linking exposure to gasoline vapors to substantially-elevated levels of testosterone in male rats. Testosterone is itself linked to violent crime in humans (Dabbs Jr et al., 1995; Birger et al., 2003). As another example, carbon monoxide may directly affect physical and cognitive functioning by binding to hemoglobin, and reducing the oxygen-carrying capacity of the cardiovascular system. This oxygen deficiency can have deleterious effects on an exposed individual. In a rare controlled 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 neuro-psychological dimensions. They found that even low level exposure results in impaired learning, attention and concentration, and visual processing. Treated individuals were – quite literally – unable to 'think straight'.

Research has also documented a positive correlation between air pollution and adverse psychological outcomes. Rotton and Frey (1984) uses data on psychiatric emergencies from the Dayton, OH police department and finds that such calls are positively correlated with levels of ozone precursors and sulfur dioxide, even when controlling for time trends and contemporaneous weather conditions. Szyszkowicz (2007) documents a similar positive correlation between emergency department visits for depression and ambient levels of a variety of pollutants, including CO, NO_2, SO_2, ozone, and $PM_{2.5}$. Further, there are several studies that find a positive association between levels of air pollution pollutants and suicide, suicide attempts, and suicidal ideation and psychiatric admission rates (Lim et al., 2012; Szyszkowicz et al., 2010; Yang et al., 2011; Briere et al., 1983; Strahilevitz, 1977).

3 Data and Preliminary Evidence

3.1 Crime Data

Our crime data come from administrative records documenting all crimes reported to the Chicago police department between 2001 and 2012 and the police departments of the Los Angeles metropolitan area between 2005 and 2013.

We obtain data on reported crimes in the Los Angeles metropolitan area from the Los Angeles County Sheriff's Department.[9] For each reported crime, the dataset provides incident date, date reported, type of crime, whether the crime was gang-related and location data in terms of the street address, geocode coordinates, and police administrative area in which the crime occurred as defined by the LASD.[10]

We obtain crime data from Chicago using the City of Chicago's open data portal.[11] The database is drawn from the Chicago Police Department's Citizen Law Enforcement Analysis and Reporting system and reports the type of crime, date, time of day, latitude and longitude of the address at which the crime was reported and other details of the incident (e.g., whether an arrest was made, whether the crime was considered domestic).

We focus on commonly-examined crimes, restricting samples in both Chicago and Los Angeles to FBI Type I crimes: homicide, forcible rape, robbery, assault, battery, burglary, larceny, arson, and grand theft auto. We separate these crimes into violent crimes (homicide, forcible rape, assault and battery) and property crimes (burglary, robbery, larceny, arson, and grand theft auto). In the Los Angeles sample, the 192,000 reported violent crimes are predominately assault (83%), while the 627,000 property crimes are predominately larceny (58%), burglary (22%) and grand theft auto (20%). In the Chicago sample, the 240,000 reported 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%).

In the Appendix, we document long-run, seasonal and intraday patterns of crime in Los Angeles and the City of Chicago that motivate this choice. As in many cities nationwide, crime and pollution have been declining over time in both Los Angeles and Chicago. Within each year, violent crime in both cities and property crime in Chicago increase during the summer months. Criminal activity also cycles over the course of each day - crime in both cities is higher during evening hours than in morning hours. As the time stamp of each crime reflects when the crime was reported, this might result in some degree of misreporting in terms of the hour (more likely) or the date (less likely). To balance concerns related to longer-run shifts in demographics and socioeconomics plausibly correlated with trends in pollution and crime and concerns related to within-day misreporting of the hour a crime occurred, we focus on daily

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[9] http://shq.lasdnews.net/CrimeStats/LASDCrimeInfo.html.

[10] The gang-related categorization is adjudged by the attending officer. Los Angeles is host to a significant level of gang violence and it is possible that the factors driving gang-violence are different from those that drive the non-gang-related events. Gang-related assaults might, for example, be more premeditated or more group-determined, in which case the loss-of-control model motivated by the literature review may be less applicable. Something less than 5% of all assaults in our dataset are gang-related. For completeness we re-estimated out main specifications including gang-related incidents in the data and it made no substantive difference to the results.

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

variations in crime and pollution.

3.2 Pollution Data

Our direct measures of ambient pollution come from the Environmental Protection Agency's network of monitors. In both cities, we will use ambient pollution data to establish a suggestive correlation with violent crime in Section 3.4. In Los Angeles, the data are also used to inform our quasi-experimental approach.

For Los Angeles, we focus on daily measures taken from the twenty-two Air Quality System stations (AQS) monitoring ozone throughout 2005-2013.[12] Pollution measures are assigned to each incident using information of the closest monitoring station. If a monitoring station fails to record pollution on a specific day the next closest station is used. Crimes that do not happen within 15 miles of a station are excluded. The mean ozone level is 0.042 ppm, with a standard deviation of 0.017. The 95th percentile day in our sample had an average reading of 0.074 across the twenty-two monitors.

For Chicago, we focus on the 24-hour average at the two PM_{10} pollution monitors consistently operating throughout 2001-2010 nearest to the center of Chicago.[13] We take a simple daily average over the hourly measurements. Monitor-days with less than 18 valid hourly readings are excluded, limiting our sample to 3642 days during the twelve-year period.The mean PM_{10} level is 28 $\mu g/m^3$, with a standard deviation of 14.4. The 95th percentile day in our sample had an average reading of 55 $\mu g/m^3$ across the two monitors.

3.3 Weather Data

The seasonality in both pollution and crime and the existing literature (e.g., Ranson (2014)) suggest that weather (particularly temperature) is an important covariate with both crime and pollution. We collect weather data for both settings from the National Climatic Data Center (NCDC). The NCDC is the most comprehensive source of publicly available U.S. weather data, reporting temperature, precipitation and other meteorologic variables at approximately 10,000 locations. We aggregate hourly data up to the daily-level and construct summary statistics similar to those used in the existing literature. Summary statistics include: (1) measures of ambient weather conditions possibly correlated with crime (daily maximum temperature, precipitation,

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[12] These stations are 06-037-0002, 06-037-0016, 06-037-0113, 06-037-1002, 06-037-1103, 06-037-1201, 06-037-1301, 06-037-1302, 06-037-1601, 06-037-1602, 06-037-1701, 06-037-2005, 06-037-4002, 06-037-4006, 06-037-5005, 06-037-6012, 06-037-9033, 06-037-9034, 06-059-0007, 06-059-1003, 06-059-2022, 06-059-5001.

[13] These stations are 17-031-1016, just west of city limits, and 17-031-0022 on the south side.

dew point, air pressure, wind speed, and cloud cover) and (2) wind direction which influences air pollution. We use weather information from the station located at Los Angeles International Airport (LAX) and Chicago Midway International Airport (MDW).[14] Wind is used to instrument for pollution in this study and Figure 1 summarizes the variation in wind direction and speed in our two samples.

3.4 Preliminary Evidence on Pollution and Crime

We begin by documenting a positive correlation between daily ambient pollution levels and violent criminal activity in both Los Angeles and Chicago.

In Los Angeles, we partition the region according to the nearest AQS and allocate the crimes to these time-invariant regions. Thus, we also include AQS (location) fixed effects to capture time-invariant heterogeneity in criminal activity. As the pollution data in Chicago is limited to a handful of stations, we aggregate crimes up to a daily, city-level time series. In both cities, we estimate,

$$Crime_{it} = \beta Pollution_{it} + \gamma X_{it} + \epsilon_{it}. \tag{1}$$

where $Crime_{it}$ is the number of crimes committed nearest to AQS i on day t; $Pollution_{it}$ is the reading at station i on day t; X_{it} is a vector of controls for weather, co-pollutants, and dummies for year-month, day-of-week, first day of the month, and major holidays.[15]

The pollutant of interest in these regressions is ozone for Los Angeles and PM_{10} for Chicago. For each city, the pollutant chosen is that which most often triggered Air Quality Index (AQI) alerts in 2010. In other words the pollutant typically 'driving' air quality problems in that region.[16] Standard errors are clustered at the year-month level to account for within-month correlation in shocks.

The results of this regression are shown in Table 2. The first four columns are results for Los Angeles data, the last four for Chicago. In the first two columns for each city, the dependent variable is the number of assaults (and batteries in Chicago due to reporting conventions) – the most common category of violent crime. There is a clear positive correlation between pollution

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[14] Midway is the closest weather station to the Chicago city center consistently reporting our meteorological variables of interest. As a comparison, we also examined similar variables at O'Hare International Airport, located approximately twice as far from the city center as Midway. Readings at Midway and O'Hare are highly correlated for all four variables. Correlation in temperatures, precipitation, wind speed and wind direction were 0.995, 0.750, 0.950 and 0.703. None of the results are sensitive to choice of weather station.

[15] Weather controls include 3-degree-C bins of maximum daily temperature and dew point, average cloud cover, wind speed, precipitation, and air pressure.

[16] In Chicago, it is in fact $PM_{2.5}$; however, we use PM_{10} due to data constraints in earlier years. The results are qualitatively similar in both cities if the actual AQI is used as the dependent variable instead.

and violent crime, even with the rich set of controls that are included. In Los Angeles, the preferred specification indicates that a one-standard deviation increase in pollution (0.016 ppm) is associated with 0.04 more assaults, or a 1.18% increase relative to the monitor-day mean of 3.39. In Chicago, the preferred specification indicates that a one-standard deviation increase in pollution (14.4 μg/m^3) is associated with 0.6 more assaults, or a 1.25% increase relative to the daily city-wide mean of 48. In Columns 3 and 7, the dependent variable is larceny – the most common category of property crime. The estimates are several times smaller in magnitude, mixed in sign, and never significant.

As a robustness check we present specifications that exclude co-pollutants (columns 2, 4, 6, 8). The Los Angeles coefficient is remarkably stable and, while it changes somewhat, the Chicago coefficient is qualitatively similar to the preferred estimate. Again, we find no significant relationship between pollution and larceny.

These results are robust across cities, but giving them a *causal* interpretation would require additional assumptions about unobservables. While we control for a wide variety of weather and time variables, there could be other time-varying unobservables affecting these results. In what follows we present quasi-experimental design adapted to the specific geographies of Los Angeles and Chicago that will allow for explicitly causal conclusions.

4 Causal Identification

The results in Table 2 showed a positive association between pollution and violent (but not property) crime. Although we control flexibly for a rich set of likely confounders, the possibility of unobserved shocks correlated with both pollution and violent crime discourage causal interpretation.

We refine our identification strategy to better address the threat of omitted variable bias, while continuing to flexibly control for factors such as weather that may be correlated with both pollution and crime. Specifically, we use wind *direction* as a source of quasi-random variation in pollution exposure. In both Los Angeles and Chicago, areas downwind of pollution sources experience higher levels of ambient air pollution. As the wind shifts from day to day, the set of downwind neighborhoods also changes.

Since we observe the location at which each crime was committed, we can compare the amount of crime in neighborhood A and neighborhood B on days when A is downwind relative to days when B is downwind. Formally, we estimate the following difference-in-differences regression, estimating crime in neighborhood *i* at time *t* as:

$$Crime_{it} = \alpha_i + \beta Treatment_{it} + \gamma_t + \epsilon_{it} \tag{2}$$

where the "treatment" denotes the wind direction that elevates pollution in neighborhood *i* on date *t*, and γ_t represents a date-of-sample fixed effect.

Our research design exploits daily, within-study-area variation in pollution, allowing us to ignore correlated unobservables related to (for instance) citywide economic activity or weather conditions. The central identifying assumption is that wind direction (which assigns "treatment") is orthogonal to within-day variation in omitted variables correlated with crime.

Our use of wind direction should also assuage any concerns about reporting bias. Crimes may be differentially under-reported, especially those that are personally sensitive. However, unless under-reporting is correlated with wind direction – and it is very difficult to think that it would be for either, let alone both, of our study areas – our inference strategy remains valid.

5 Quasi-experimental Evidence: Los Angeles

The Los Angeles basin has an unusual topography, that we exploit. When the wind blows from the west or southwest, pollution from the whole basin area (including the major point sources of Los Angeles International Airport (LAX) and the Port of Los Angeles) is carried inland.[17] The dirty air is then "pinned" over downtown Los Angeles, and the San Gabriel and San Fernando valleys against the "cushion" of high land a few miles to the east and northeast. This process is well-understood by students of air quality in the city. McCarty (2014) writes that "(t)he high density of transportation, with cars, air traffic and shipping produces volatile organic compounds and oxides of nitrogen – the chemicals that turn into ozone. Sea breezes push them over the basin and the abundant sunlight transforms them into ozone, which is then trapped by the mountains to the east". Suzanne Paulsen, Director of the UCLA Center for Clean Air aptly sums it up: "The Los Angeles basin is unfortunately uniquely suited to ozone pollution. It's a combination of the ring of mountains, wind direction and lots of sources upwind that produces the high ozone" (quoted in McCarty, 2014).

Helpfully for us - and as this description of the underlying process implies - the effect of a wind blowing off the sea is not uniform across the area. In particular, such a wind cleanses

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[17] The combined ports of Los Angeles and Long Beach are the largest in the US and third largest in the world, and represent the single largest contributor to air pollution in the Los Angeles Metropolitan area (Polakovic, 2002)

the air of locations between the coast and downtown (except those directly adjacent to major pollution sources on the coast that we have already identified), but dirty the air over the downtown area of LA and those communities to the east and north-east (Schultz and Warner, 1982; Lu and Turco, 1996, 1994; Lu et al., 2003).[18] The blanket of pollution that settles between the city and the mountains can easily be seen in an aerial picture such as Figure 2, taken from the south-west on a day when the wind is blowing from the sea.[19] It shows the population centers in the San Fernando and San Gabriel Valleys – in addition to the downtown core of LA – sitting under a shroud of polluted air.[20]

We exploit the differential effect of a wind direction on air quality in different communities in our design. In some places, like the city of Pasadena, a wind from the west sharply diminishes air quality. In others, such as the city of Pomona, a wind from the west cleans the air. In essence, we compare crime in locations like Pasadena relative to locations like Pomona on days in which the wind is "treating" Pasadena relative to days in which it is not.

We first show that westerly winds increase ambient air pollution at inland monitors proximate to the San Gabriel mountains relative to monitors near the coast.[21] For each AQS, we regress daily ozone measured at that AQS on wind direction dummy which takes the value 1 if the prevalent wind on the day in question is recorded as having come from a direction between 240 degrees (roughly SW) 276 degrees (roughly W) and 0 otherwise. We further include daily weather controls (daily mean temperature, humidity, precipitation, wind speed, air pressure and cloud cover) and time fixed effects (day of week, year-month, holiday and pay day dummies) plausibly correlated with both air pollution and wind-direction. [22]

Table 3 reports the location-specific coefficients on the westerly-wind treatment dummy for each of the AQS monitors. We also summarize the spatial variation in Figure 3. Note that

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[18] As they found in their sampling study: "A few hours into the sea breeze regime, the highest concentrations of secondary pollutants were found in the San Gabriel Valley. In the source areas of the coastal plain, concentrations fell as ... air was displaced by air of more recent marine origin" (Blumenthal et al., 1978, p. 896)

[19] The major highway in the photograph is Interstate 110 (The Harbor Freeway) which runs due north before bearing rightward towards LA downtown. The area immediately to the left of the "elbow" in the freeway is the eastern edge of the University of Southern California (USC) campus. The white circular building towards the bottom left corner is the LA Memorial Sports Arena – former home to the LA Lakers basketball team, and soon to be demolished to provide a site for a soccer stadium for the MLS expansion franchise Los Angeles FC.

[20] In a well-cited early study, Blumenthal et al. (1978) provides extensive additional commentary on the atmospheric science that underlies the differential impact of sea breezes on pollution in different parts of our study area.

[21] It is worth noting that the mechanics of air quality in the region mean that the levels of the main pollutants tend to move together. If polluted air is held in the valleys then that air holds elevated levels of the various pollutants. Though we develop our results for ozone, the most frequently problematic pollutant in the study area, our method will not allow us convincingly to disentangle the role of ozone from correlated pollutants. The story in this part of the paper is more akin to a "bad air" effect than isolating a particular effect of ozone.

[22] To avoid complication we will also use "westerly" as a shorthand descriptor for such a wind, but acknowledge here that this nomenclature is inexact. The 36 degree bin width divides the circle into 10 parts, but our results are not sensitive to the choice of bin widths, as we report later.

pollution in downtown LA (AQS 5), as well as population centers close to the mountains (such as Pasadena (11), Burbank (4), Reseda (6), Asuza (1), Glendora (2)), is elevated on west-wind days as pollution from the whole area is pinned by the breeze off the sea against the cushion of higher land. Pomona (10) is far enough east that the mountain range does not act as a cushion for wind from the west-southwest. Santa Clarita (15) sits at the southwest entrance to the Antelope Valley, a low-lying passage around 6 to 8 kms in width between the San Gabriel Mountains to the east and Santa Monica Range further to the west. This allows escape of air from the southwest and pollution is blown further inland and as the air slows deposited around Lancaster (16) at the other end of the valley. The regressions confirm the established wisdom that population centers near the coast, such as Anaheim (18), Irvine (20) and Playa del Rey (14), have cleaner air when the wind is primarily blowing off the sea. The cluster of stations in the immediate vicinity of the Port of Los Angeles ((7), (8), (12) and (13)) and other industry in the Harbor area are exceptions; however, our results are robust to the inclusion or exclusion of these stations.

We use the sign of the coefficient on the wind direction dummy in these 22 "first-stage" regressions to divide the daily crime sample into eleven AQS locations where a wind off the sea causes an increase in pollution concentrations (where the regression of pollution on a westerly wind results in a positive coefficient) and eleven in which it causes a decrease. A treated observation is defined as a west-wind day at an AQS location where westerly wind is associated with higher pollutant concentrations. More precisely, we estimate the following equation:

$$Crime_{st} = \beta_0 + \beta_1 Treatment_{st} + W_t \beta_2 + \alpha_s + \gamma_t + \epsilon_{st}$$

where "treatment" is a dummy variable equal to one as described above. The vector α_s contains station fixed effects that control for any time-invariant unobservable AQS-specific factors. The vector γ_t contains date fixed effects, which absorbs any day-to-day variation in economic and weather conditions, as well as any other unobserved factors common across the metro area that might be correlated with wind direction. We also run a specification omitting the date fixed effects, but including a flexible set of weather controls.[23] These controls are co-linear with the date fixed effects in our main specification.

The coefficient of interest is that on the treatment dummy. In effect, the regression is a difference-in-differences specification. First, at those locations where a west-wind is associated

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[23] When included, the vector W contains weather controls (daily mean temperature, humidity, precipitation, wind speed, air pressure and cloud cover). We again control flexibly for temperature and humidity by means of a set of 3 degree Celsius indicators for temperature and dew point temperature.

with higher pollution we would expect to see more crime – other things being equal – on west-wind (treated) days than non-west-wind (untreated) days. Second, on west-wind days we should expect, other things being equal, to see a most pronounced rise in crime in those places where such a wind is associated with higher pollution, compared to locations where it is not. A positive coefficient would provide evidence of a causal impact of air pollution on violent crime.

5.1 Results

The result from the base specification is summarized in column 1 in Table 4. Of the 72,182 data points, 17,719 (24.6 %) are treated. The coefficient of interest is 0.162, positive and significant at the 5% level. Recall that the coefficient being positive indicates there is an increase in incidents of violent crime in the treated set with the untreated set as a comparator. This amounts to a 6.14 percent increase in the total daily count of assaults in a treated compared to untreated state.

Column 2 gauges sensitivity of our results to the exclusion of date fixed effects. The point estimates are somewhat changed, but remain positive and significant at the 5% level. Weather variables might have an important direct impact on criminal behavior – by affecting mood, or the types of activity in which people engage – while also directly influencing air quality conditions. In column 3 we again omit date fixed effects but retain the suite of weather controls. The point estimate changes slightly but remains positive and significant. Comparison of results suggests that weather controls account for much of the impact of including date fixed effects, which is unsurprising.

As noted the areas near the port are somewhat anomalous. In column 4 we report coefficients from our preferred specification, excluding all data from the port AQSs (numbers (7), (8), (12) and (13)). Again the sign of significance of the coefficient on the treatment dummy is maintained.

Table 5 presents the results of the same specification for larceny. As shown the point estimates are much smaller (especially relative to the mean) and statistically insignificant, indicating that there is no effect of pollution on larceny crimes. This is again consistent with pollution inducing violent behavior in particular rather than criminality in general.

In defining whether a day has “westerly” wind, we chose 36 degrees as our bin width, dividing the circle into 10 equal sectors. Table 6 shows the result of re-estimating our preferred specification on wind direction defined by alternative bin widths: 45, 60, 75 and 90 degrees. It can be seen that such variation has no substantive effect on the results.

5.1.1 Lags

Various studies suggest serial correlation in crime (Jacob et al., 2007; Matsueda and Anderson, 1998). If wind direction and crime are both correlated over time, then we would expect to see a relationship between them. Further, there could be negative autocorrelation, in which pollution "harvests" crimes that were would have happened one or two days later instead.[24] To address these concerns, Table 7 allows for the possibility of lagged effects of treatment and crime by including up to three lagged days of crime and treatment variable. As shown although there exists positive autocorrelation in criminal behavior, the point estimates of coefficient of interest are not disturbed. We also find a smaller but still significant lagged treatment effect, consistent with pollution exposure having some effect that carries over from one day to the next (but no longer).

5.1.2 Placebos

Table 8 summarize the result of four separate placebo tests using, in turn, treatment 100 days before the date in question, treatment 100 days after, and treatment defined by wind direction in New York and Houston, respectively. The point estimates are mixed in sign, several times smaller than the point estimate from our preferred specification, and do not approach statistical significance at conventional levels.

6 Quasi-experimental Evidence: Chicago

We bolster evidence from the Los Angeles by replicating the spirit of the exercise in Chicago, with changes in wind direction generating plausibly exogenous variations in air quality, but with analysis conducted at a much more local level. In particular we look at neighborhoods on either side of major interstates on days on which the wind blows from one direction or the other. In effect the downwind locations on any given day are treated, the upwind locations serve as controls. This approach means that our treatment and control areas experience virtually identical variations in economic activity, weather and other observed or unobserved correlates of criminal behavior. Despite the different strategy for selecting treatment and control areas, we find qualitatively identical results. Violent crime (but not property crime) increases on the side of the interstate that happens to be downwind on any particular day.

To demonstrate the downwind pollution impact of an interstate, consider Figure 4 which

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[24] Given the mechanisms at play, such as loss of impulse control, this does not seem likely *ex ante*.

summarizes CO readings at one of the monitors in Chicago (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. 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.

Our identification strategy is easiest to illustrate again using I-290 as an example. I-290 runs (essentially) due west through 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. 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 this to 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 5 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 5 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. While the airport is technically part of the City of Chicago, it is connected to the rest by only a narrow strip of highway, and is unlikely to be representative of criminal activity elsewhere. The southeastern part of the city borders Lake

Michigan to the east and Lake Calumet to the southwest; 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 our base 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.[25] We relax both of these modelling choices later in the paper.

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 control for day-to-day variation in local criminal activity. It is important to note that since the interstates in Chicago run in different directions the treatment of neighborhoods by pollution from those highways is driven by *different* wind directions. Any unobservable or omitted influence on violent crime would have to be correlated with wind direction in a very particular and complex manner to threaten our causal interpretation.

6.1 Results

We present main results for violent crime in Table 9. Column 3 corresponds to the specification in equation (3).[26] 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

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

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

per route-side per day), this represents an increase of approximately 2.2 percent. Columns 1 and 2 report the effect of excluding subsets of controls.

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.

This seems a remote threat to identification. 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, to 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 temperature 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 10 presents the results of identical specification for property crime rather than violent crime. Again we find no evidence that pollution impacts property crime.

Two modeling choices underpin the results in Table 9. 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. Table 11 presents the results of estimating

Equation (3) as we vary those two inclusion criteria. 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. The preferred specification (that in column 4 from Table 9) is highlighted in bold.

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. 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.[27]

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.[28] 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.

As noted in the Los Angeles analysis, crime and pollution may be autocorrelated. 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.

6.1.1 Results from an alternative identification strategy

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

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[27] As an extension to this idea, in Appendix A.2.2 we demonstrate that the downwind effect of pollution is strongest and most cleanly estimated on days during which the wind is blowing between 5-10 miles per hour. On these days, the wind is sufficient strong to ensure that the pollution is pushed to one side of the road, but insufficiently strong to disperse the pollution quickly.

[28] 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.

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 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 strikingly 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.

6.1.2 Placebo Test

As a final piece of evidence, we consider a placebo test of our identification strategy. To motivate the placebo test, consider the following thought exercise. Suppose we did not know *ex ante* the latitude at which I-290 cuts straight east/west through the city of Chicago. We could estimate downwind coefficients from our model at a number of different latitudes. We could then examine whether the effect on violent crime of being downwind was greatest at the latitude of I-290. If we found large effects at alternative latitudes, we might worry that our downwind treatment was capturing effects other than pollution from mobile sources.

To conduct the exercise, we focus on 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 6 maps the latitude and longitudes of the crimes we use for the falsification test in green and the location of the interstates in red. Moving from the south to the north in one mile increments, we consider alternative latitudes 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 7 plots the difference in the north-south violent crime differential on days when the wind is blowing to north rather than 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 9, although this exercise only examines one of the seven interstate segments.

Three points in particular stand out in Figure 7. 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.

7 Broader Implications

We establish evidence that increases in ambient pollution causes an uptick in violent crime. This has two clear policy consequences. First, a Pigouvian tax or external cost estimate for local pollutants excluding the cost of crime would be understated. Second, the cognitive and behavioral effects of pollution exposure may include a much wider range of outcomes and decisions than previously thought.

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

Using our estimates of the effects of pollution on crime in Chicago, we compute a back-of-the-envelope estimate of the cost of mobile pollution-induced crime. We apply cost of crime estimates from the literature, assuming that all the additional crimes are assaults and batteries to be conservative.[29] Then we scale our estimates up to the size of the urbanized population of the United States. Under these assumptions, the annual cost to the United States amounts to $178 million per year. For 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.

Willingness-to-pay estimates from the stated and revealed preference literatures can also help describe the general magnitude of the effect. Bishop and Murphy (2011) apply a hedonic model to LA housing data, and estimate that mean willingness to pay for a 10% in violent crime is 472 USD (2010) per household per year. Taking the 6.1% increase from our LA estimates, this suggests a willingness to pay of somewhere around 250-300 USD (2010) to eliminate the crime we estimate to be pollution-induced.

Although we cannot put an exact number on the cost of pollution-induced violent crime, it is robustly positive, and appears to be economically significant. Translating any of these calculations directly to the appropriate adjustment to Pigouvian tax is difficult, given that we identify the effect off of the difference between ”good” and ”bad” air days. Still, they demonstrate that the pollution-crime externality is non-trivial, and should be considered in future research and policy decisions.

We do not take a stand on the exact underlying mechanism, but our results suggest that air pollution may impact behavior in economically-meaningful ways much more broad than previously considered. Although we focus on violent criminal activity as an outcome, the potential underlying loss of control and increased impulsivity may be related to other economically important decisions, summarized broadly in Kahneman (2011). These results also provide insight into potential behavioral explanations behind lost productivity and performance found by previous studies. Finally, we see our results as complementary to the literature on the cognitive effects of poverty (e.g., Mani et al., 2013; Schilbach et al., 2016), in which cognitive load and stress lead to poor decisionmaking. Pollution exposure may have similar effects, which adds an additional dimension of concern to policy debates about environmental justice and high

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[29] Details of the calculation are in Appendix A.3.

levels of pollution in the developing world.

8 Conclusion

The primary contribution of this paper is to identify - for the first time - a causal link from short-run variation in air pollution to violent crime. Our approach exploits variation in air quality induced by naturally occurring changes in wind direction in two heavily-populated parts of the United States. In the Los Angeles basin, a wind blowing from the west "treats" only some communities with polluted air; this is determined by the specifics of local topography. In Chicago, wind orthogonal to a major interstate such as the I-290 treats those neighborhoods on the downwind side with pollution from highway users, but not those upwind. Each setting lends itself to a design similar to a difference-in-differences estimator.

The analyses in both Los Angeles and Chicago provide evidence of a causal link from elevated air pollution in an area to higher same-day incidence of violent crime in that area. The effect can persist from one calendar day to the next, though the size of any lagged treatment effect is small. We find no evidence of any effect on property crime. As such this seems to be a story about violence - not criminality in general - consistent with the literature in other disciplines on air pollution and aggression.

The size of the estimated effects are substantial. In our preferred specification in Los Angeles a treated community experiences a 6.14% increase in the incidence of violent crime. In Chicago violent crime increases by 2.2% in a neighborhood on the downwind side of a major interstate. Back of the envelope calculations based on these magnitudes suggest that the cost to society is meaningful compared to other outcomes studied in the external costs literature.

To our knowledge, this is the first paper documenting a causal relationship between ambient pollution and crime. As such it is appropriate, within each setting, to subject the central estimates to a wide variety of robustness and falsification tests. However, we also contend that each setting acts to corroborate the results of the other, and that the pair of case studies – generating congruent results – are more persuasive in combination than either would be individually. Concerns regarding idiosyncratic threats to identification that might arise in one setting can be allayed by the consistency of results from the other.

While we are unable to provide positive evidence on the underlying mechanism, our results suggest that air pollution may impact behavior in economically-meaningful ways much more broad than previously considered. From a policy standpoint, the analysis points to an additional social cost of air pollution. Estimates of the marginal social cost of air pollutants that ignore it can be expected to understate the social benefit of pollution control interventions. Thus, benefit-cost analysis based on such estimates will prescribe environmental policies that are insufficiently stringent.

More generally our work contributes to the growing recognition that, in addition to the well-understood health benefits, a clean natural environment contributes to a much wider range of positive economic and social outcomes.

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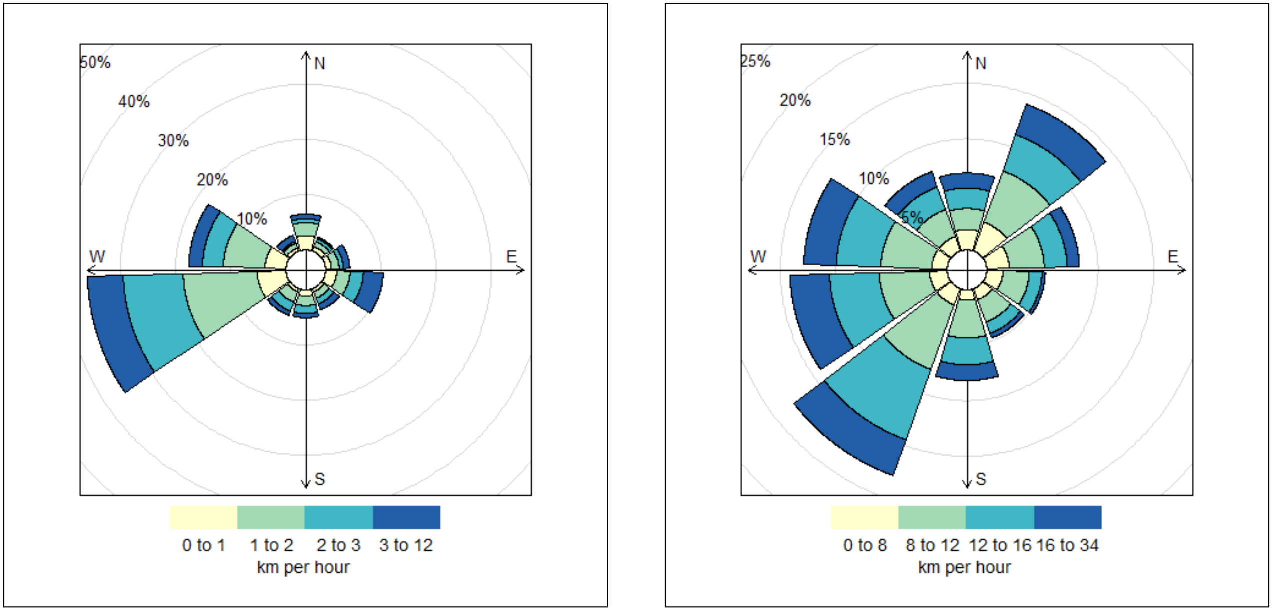
9 Tables and Figures

Figure 1: Distribution of wind source direction



Panel A: Los Angeles

Panel B: Chicago

Figure 2: Los Angeles from the southwest

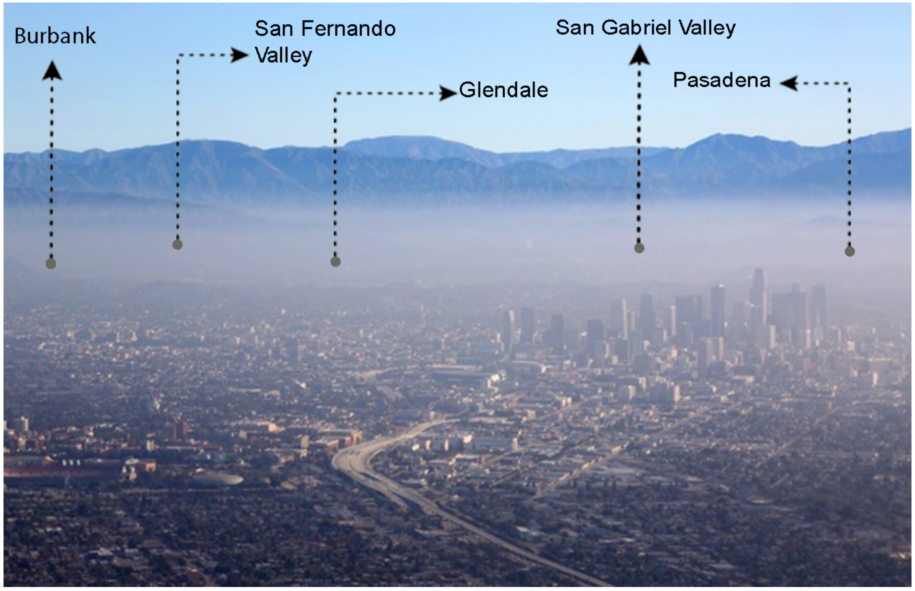


Figure 3: Positive vs. Negative AQSs

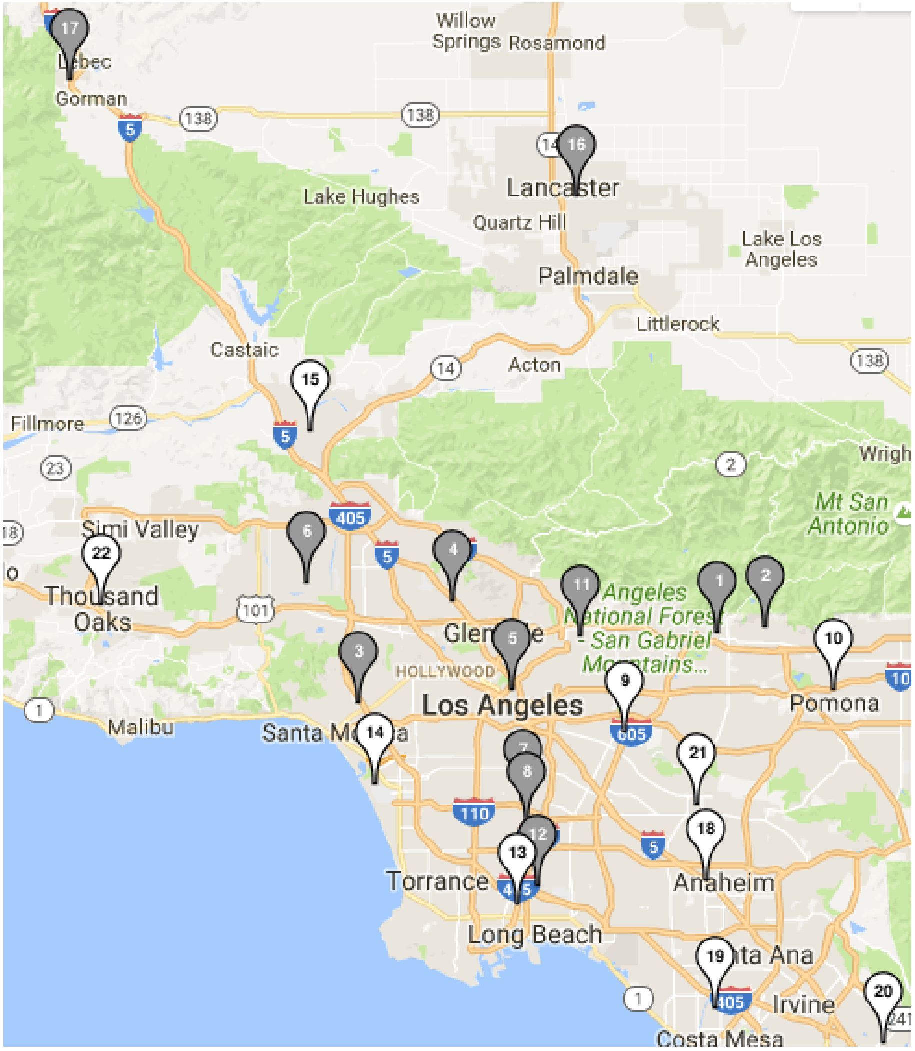


Figure 4: Average CO reading near I-290, by wind direction and vector-based speed

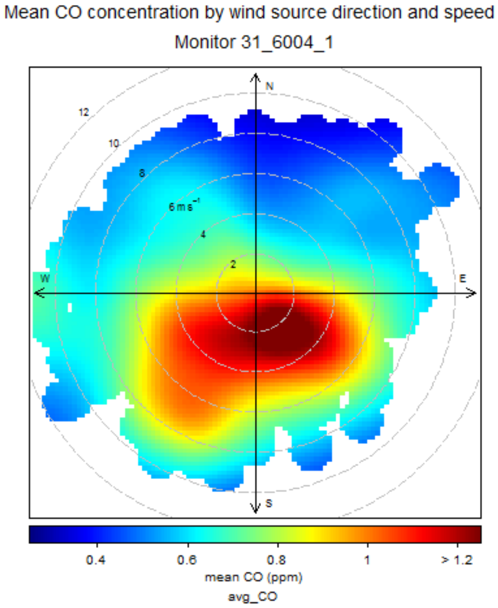


Figure 5: Chicago: Sample set for interstate identification strategy

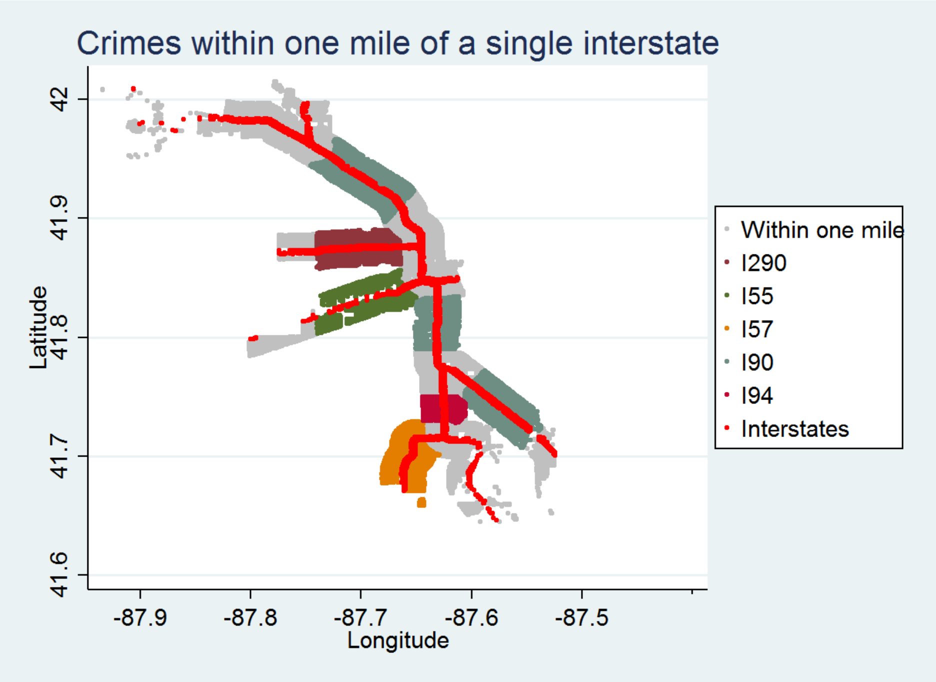


Figure 6: Chicago: Sample set for falsification test

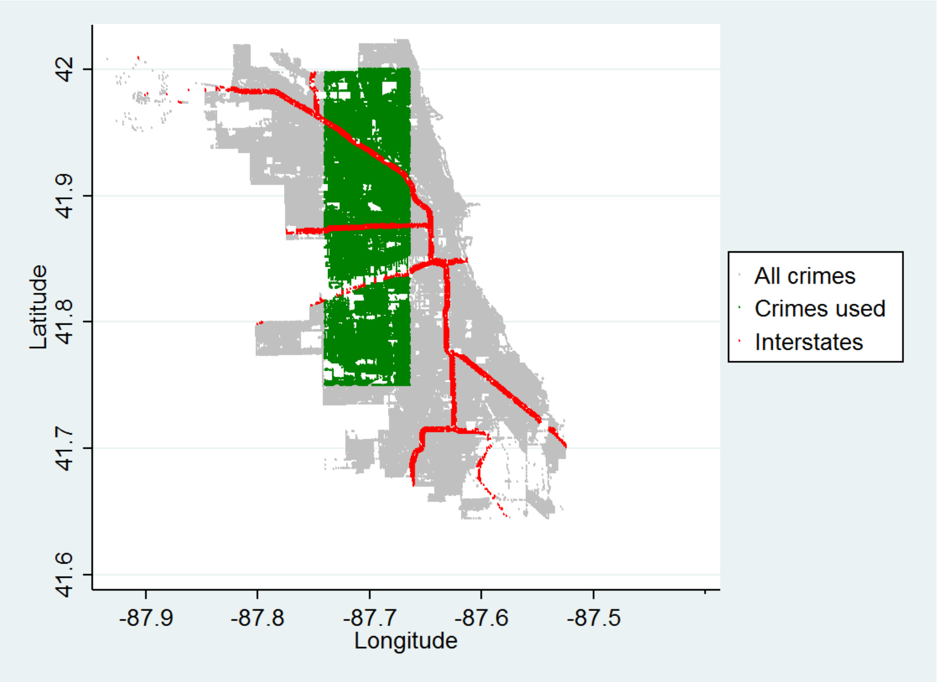
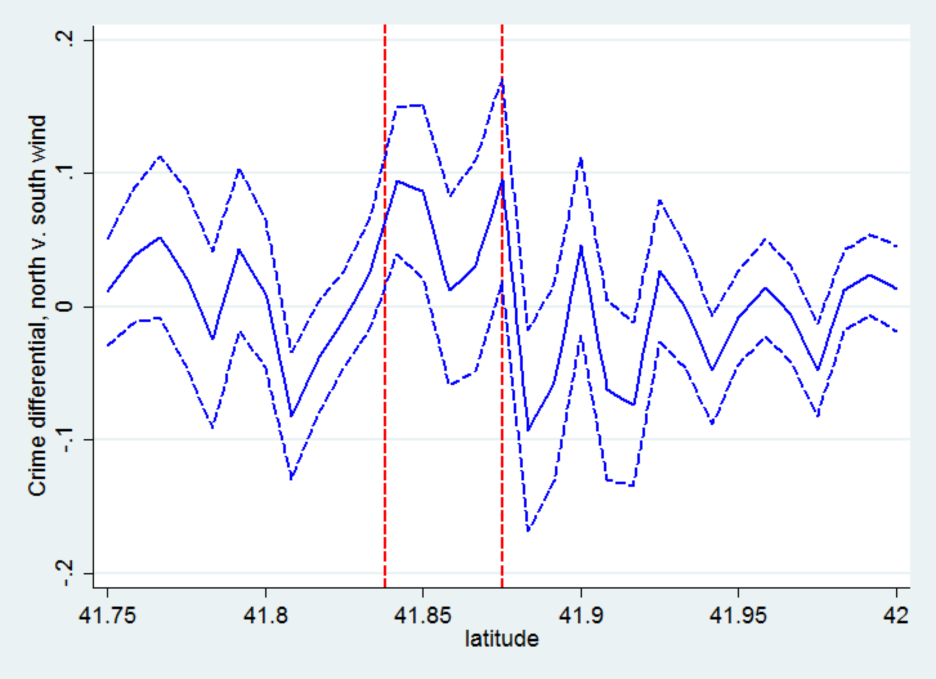


Figure 7: Chicago: North-south crime differential, alternative latitudes



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

Table 1: Summary statistics

	Los Angeles		Chicago	
	Mean	Std. Dev.	Mean	Std. Dev.
Citywide sample:				
Number of dates	3383		3642	
Daily city-wide assault/battery	60.58	12.21	51.0	16.6
Daily city-wide larceny	96.80	20.85	244.3	47.4
Precipitation (mm)	0.87	4.67	2.75	7.74
Maximum temperature (°C)	23.85	5.12	15.5	11.6
Daily avg. carbon monoxide (ppm)	0.68	0.50	0.59	0.27
Daily avg. NO2 (ppm)	0.035	14.41	0.027	0.0084
Daily avg. ozone (ppm)	0.044	0.018	0.023	0.012
Daily avg. PM10 ($\mu g/m^3$)	26.40	11.56	27.7	14.4
Wind speed (km/h)	2.53	1.62	12.3	4.35
Dew point (°C)	11.96	4.20	4.43	10.1
Air pressure (hpa)	1014.82	3.87	1016.6	7.08
Cloud cover sunrise to sunset (percent)	23.74	24.91	63.8	27.7
Los Angeles treatment sample:				
monitor-days	72182			
Daily monitor assault	2.65	3.39		
Daily monitor larceny	4.28	4.54		
Chicago Interstate sample:				
Interstate-side-days			41730	
Daily interstate-side violent crimes			1.1	1.4
Daily interstate-side property crimes			7.3	5.2

Sources: Crime data from the Los Angeles County Sheriff's Department and Chicago Police Department. Weather data from the US National Climatic Data Center (US-NCDC). Pollution data from the U.S. Environmental Protection Agency.

Table 2: Preliminary evidence on the correlation between pollution and crime

	Los Angeles: Ozone				Chicago:PM10			
	Assault		Larceny		Assault & Battery		Larceny	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Preferred	No Co-pollutant Controls	Preferred	No Co-pollutant Controls	Preferred	No Co-pollutant Controls	Preferred	No Co-pollutant Controls
Main Pollutant	2.488**	2.809***	-0.810	0.869	0.042**	0.078***	0.0070	-0.0073
	(1.001)	(0.939)	(1.372)	(1.324)	(0.018)	(0.019)	(0.040)	(0.047)
Controls for weather	X	X	X	X	X	X	X	X
Controls for co-pollutant	X		X		X		X	
Time FE	X	X	X	X	X	X	X	X
AQS fFE	X	X	X	X				
Observations	69388	69388	69388	69388	3642	3642	3642	3642
R-Squared	0.750	0.751	0.743	0.765	0.73	0.73	0.81	0.81

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered by year-month are in brackets. Weather controls include measures for maximum temperature (3 degree C indicators), dew point (3 degree C indicators), cloud cover, wind speed, air pressure and precipitation. Co-pollutant covariates include nitrogen dioxide, carbon monoxide and PM_{10} (LA) / ozone (Chicago). Time dummies include day of week, year-month, first-of-the-month and holidays dummy. All environmental variables are the mean of daily values.

Table 3: LA: Effect of Westerly Wind on Ozone by AQS

	(1) Azusa	(2) Glendora	(3) Sawtelle	(4) Burbank	(5) LA Downtown	(6) Reseda	(7) Lynwood	(8) Compton
West	0.00126**	0.00121	0.000458	0.000956	0.000458	0.00106**	0.00585**	0.00126***
	(0.000584)	(0.00102)	(0.000330)	(0.00100)	(0.000437)	(0.000454)	(0.00294)	(0.000447)
Observations	2900	2900	2900	2900	2900	2900	1750	1370
R-Squared	0.743	0.784	0.595	0.766	0.714	0.732	0.749	0.707
	(9) Pico Rivera	(10) Pomona	(11) Pasadena	(12) Long Beach	(13) Lower Westside	(14) Playa Del Rey	(15) Santa Clarita	(16) Lancaster
West	-0.00135**	-0.000458	0.00527**	0.00224***	-0.000783	-0.00300***	-0.00123***	0.00527**
	(0.000621)	(0.000471)	(0.00225)	(0.000338)	(0.000601)	(0.00112)	(0.000417)	(0.00220)
Observations	2600	2900	2900	2900	2900	2900	1430	2900
R-Squared	0.765	0.744	0.800	0.723	0.662	0.632	0.546	0.737
	(17) Lebec	(18) Anaheim	(19) Mesa Verde	(20) Irvine	(21) La Habra	(22) Thousand Oaks		
West	0.000197	-0.0000691	-0.00140***	-0.000419	-0.00123**	-0.000148		
	(0.000382)	(0.000342)	(0.000539)	(0.000552)	(0.000622)	(0.000555)		
Observations	513	2900	1318	2900	2900	2900		
R-Squared	0.776	0.727	0.654	0.563	0.583	0.722		
Controls for weather	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Dependent variable is ozone. Standard errors clustered by year-month are in brackets. Weather controls include measures for maximum temperature (3 degree C indicators), dew point (3 degree C indicators), cloud cover, wind speed, air pressure and precipitation. Time dummies include day of week and year-month. All environmental variables are the mean of daily values.
* significant at 10% ** significant at 5% *** significant at 1%.

Table 4: LA: Assault

	(1)	(2)	(3)	(4)
Treatment (West*Location Dummy)	0.162***	0.242***	0.175***	0.0919***
	(0.0302)	(0.0605)	(0.0405)	(0.0352)
Controls for weather			X	
Date FE	X			X
AQS FE	X	X	X	X
Observations	72182	72182	72182	62339
R-Squared	0.748	0.725	0.728	0.728

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered by year-month are in brackets. Weather controls include measures for maximum temperature (3 degree C indicators), dew point (3 degree C indicators), cloud cover, wind speed, air pressure and precipitation. Co-pollutant covariates include PM_{10}, nitrogen dioxide and carbon monoxide. Column 4 excludes port monitoring stations including AQS numbers (7), (8), (12) and (13).

Table 5: LA: Larceny

	(1)	(2)	(3)
Treatment (West*Location Dummy)	0.0625	0.0518	0.0612
	(0.0504)	(0.0628)	(0.0489)
Controls for weather			X
Date FE	X		
AQS FE	X	X	X
Observations	72182	72182	72182
R-Squared	0.742	0.721	0.722

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered by year-month are in brackets. Weather controls include measures for maximum temperature (3 degree C indicators), dew point (3 degree C indicators), cloud cover, wind speed, air pressure and precipitation. Co-pollutant covariates include PM_{10}, nitrogen dioxide and carbon monoxide. All environmental variables are the mean of daily values.

Table 6: LA: Assault, by treatment angle

Angle width	36	45	60	75	90
Treatment	0.162***	0.165***	0.173***	0.176***	0.174***
	(0.0302)	(0.0306)	(0.0303)	(0.0296)	(0.0297)
Date FE	X	X	X	X	X
AQS FE	X	X	X	X	X
Observations	72182	72182	72182	72182	72182
R-Squared	0.748	0.748	0.748	0.748	0.748

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Dependent variable is daily number of assaults. Standard errors clustered by year-month are in brackets. Time dummies include date fixed effect. All environmental variables are the mean of daily values.

Table 7: LA: Assault, including lagged variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	0.165***	0.141***	0.137***	0.134***	0.128***	0.125**	0.125**
	(0.0405)	(0.0280)	(0.0275)	(0.0272)	(0.0269)	(0.0269)	(0.0269)
Treatment, t-1		0.0951***	0.0892***	0.0848***	0.0741**	0.0711**	0.0697**
		(0.0293)	(0.0280)	(0.0276)	(0.0274)	(0.0271)	(0.0270)
Treatment, t-2			0.0303	0.0230	0.0160	0.00926	0.00719
			(0.0328)	(0.0323)	(0.0324)	(0.0323)	(0.0323)
Treatment, t-3				0.0396	0.0375	0.0328	0.0281
				(0.0241)	(0.0240)	(0.0241)	(0.0240)
Number of crimes, t-1					0.0858**	0.0808***	0.0787***
					(0.00755)	(0.00702)	(0.00691)
Number of crimes, t-2						0.0582***	0.0553***
						(0.00668)	(0.00656)
Number of crimes, t-3							0.0365***
							(0.00600)
Date FE	X	X	X	X	X	X	X
AQS FE	X	X	X	X	X	X	X
Observations	72182	72182	72182	72182	72182	72182	72182
R-Squared	0.748	0.748	0.748	0.748	0.750	0.751	0.751

Notes: *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is daily number of assaults. Standard errors clustered by year-month are in brackets. All environmental variables are the mean of daily values.

Table 8: LA: Falsification

	(1) -100	(2) +100	(3) New York	(4) Houston
Treatment (West*Location Dummy)	0.0338	0.00268	0.00023	0.0234
	(0.0310)	(0.0294)	(0.0410)	(0.0313)
Date FE	X	X	X	X
AQS FE	X	X	X	X
Observations	72182	72182	72182	72182
R-Squared	0.748	0.749	0.778	0.698

Notes: *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is daily number of assaults. Standard errors clustered by year-month are in brackets. Time dummies include date fixed effect. All environmental variables are the mean of daily values.

Table 9: Chicago: 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 10: Chicago: 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 11: Chicago: Downwind violent crime, by treatment angle and distance from interstate

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

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

Table 12: Chicago: 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: Chicago: 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.

A Appendix

A.1 Supplementary Tables and Figures - Los Angeles

A.1.1 Patterns of Crime in Los Angeles

Figure 8 shows hourly pattern in assault and larceny in Los Angeles. As shown assaults are lowest in the early morning and tend to increase until midnight. Larceny theft crimes are also at lowest rate in the early morning, they increase until evening but tend to decrease after that.

A feel for the seasonal variability in crime incidents is provided in Figure 9. Assaults are concentrated in the hotter, more polluted months of May to August while the larcenies are more up-and-down through the year. Normalizing crimes level in 2005 to 100, Figure 10 depicts the annual trends in assaults and larcenies between 2005 and 2013. As it is clear, both group of crimes have decreasing trend since 2005. Finally Figure 11 gives an impression of seasonality of pollutants in Los Angeles. Ozone exhibits a strong seasonal pattern, with higher levels in summer. CO exhibits the opposite pattern, with higher levels in winter.

Effects by wind power Not only wind direction but also wind speed plays an essential role in determining pollution concentrations in a city. Although we control for wind speed in our estimations, we test the effect of wind power in Table 14 by interacting our treatment variable by wind bin. This allows us to compare a light west wind day with a strong west wind day. As shown, winds between 4 - 6 meters per second have the larges, positive and statistically significant effect on daily number of assaults in treated area. In addition, strong winds do not have any significant effects on assault incidents.

Effects by season In Table 15 we interact our treatment variable by each season with reference season is winter. This is a suggestive approach allowing us to determine the most influential pollutant. As indicated, across all specifications point estimates are largest during summer months suggesting ozone is the primary pollutant affecting assault incidents.

Effects by day of week Although we include date fixed effect in our estimation, our point estimates show the individuals average behavior for a specific day. In Table 16 we interact our treatment by day of week to allow the effect of treatment to vary by weekday versus weekends. As presented, our results are driven on weekends suggesting that the positive effect of pollution on assaults can be augmented by higher number of people spending time in outdoor activities on weekends.

A.2 Supplementary Tables and Figures - Chicago

A.2.1 Patterns of Crime in Chicago

Crime reports display certain temporal and seasonal regularities. As is clear from Figure 12, 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 13, 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 14 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 12 and 13, 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 15 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.

A.2.2 Supplementary evidence

Effects by wind strength As is clear from Figure 4, pollution on one side of a major interstate is correlated with both wind direction and wind speed. In particular, on calm days, we see pollution rises regardless of the direction of the breeze. This is due to the fact that without sufficient wind, pollution will 'pool' along both sides of the interstate. In addition, if the wind is sufficiently strong, the wind may disperse pollution sufficiently so as not to have a meaningful impact on exposure immediately downwind of the highway.

In Table 17, we estimate separate downwind coefficients by wind-bin. In this way, we compare the effect of being downwind on a calm day, a day with a light wind that pushes but does not meaningfully disperse pollution, and days with strong winds that spread pollution from a highway beyond the area immediate proximate to the road. We find patterns roughly in line with the air transport predictions above. Winds between 2-4 meters per second (5 - 10 miles per hour) are associated with the largest, statistically precise impact of being downwind. Although strong winds are associated with larger point estimates, the point estimates are very imprecisely estimated due to the small fraction of days during which wind speeds average more than 20 miles per hour over the course of the day.

Effects by 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 18 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."[30]. 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 19) results confirms that there is no effect within any particular type of crime that is being obscured by an opposite response among another type.

Effects by season 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 9 to vary by season. We report the coefficient for the season-specific treatment effects in Table 20. 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.

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

Effects by 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.[31] 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 21. 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 location during the week, introducing measurement error into treatment effect and attenuating the effect of pollution on crime.

A.3 Cost of Crime Calculation based on Chicago Estimates

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.[32]

In constructing our sample, we omit 48% of the crimes that occur within one mile of an interstate.[33] However, in calculating the total cost of pollution, we want to include these areas.[34] If we assume that each of the classes of violent crimes increase differentially according to the

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[31] 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.

[32] 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.

[33] As we note in Section 6, 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.

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

estimates from Table 18, 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.

A.4 Appendix Figures and Tables

Figure 8: Crime share by hour of day, Los Angeles

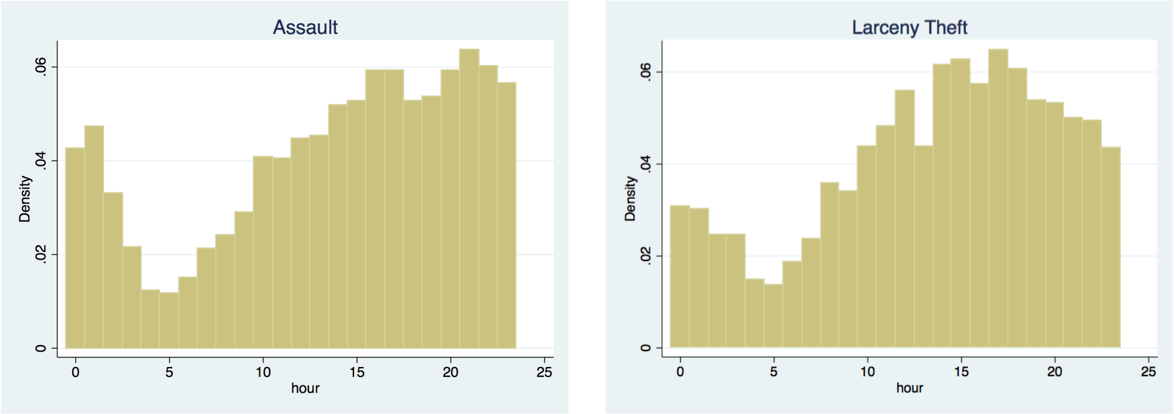

Figure 9: Average crimes by week of year, Los Angeles

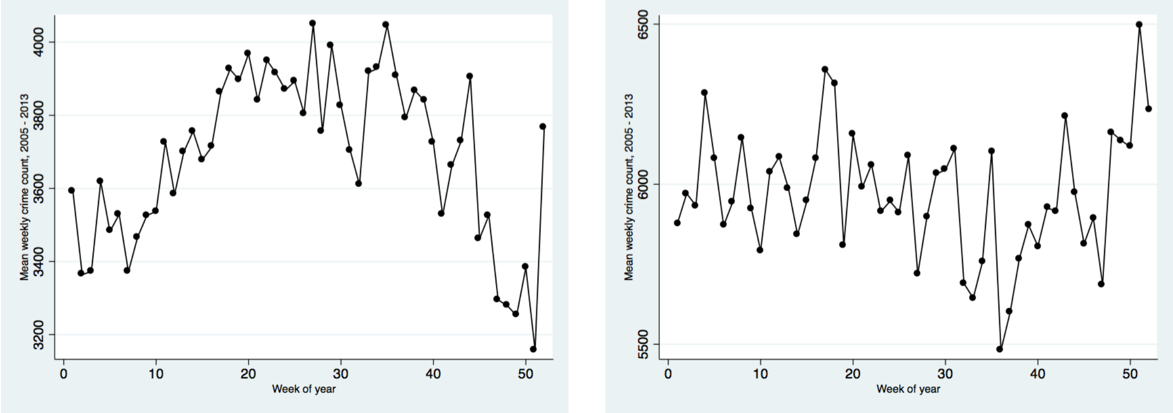

Figure 10: Normalized average annual crimes (2005 levels = 100), Los Angeles

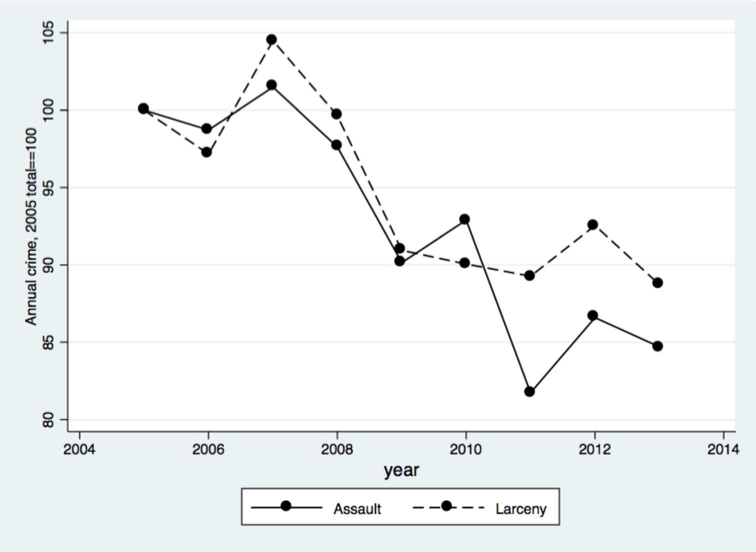

Figure 11: Seasonality in Ozone and CO emissions , Los Angeles

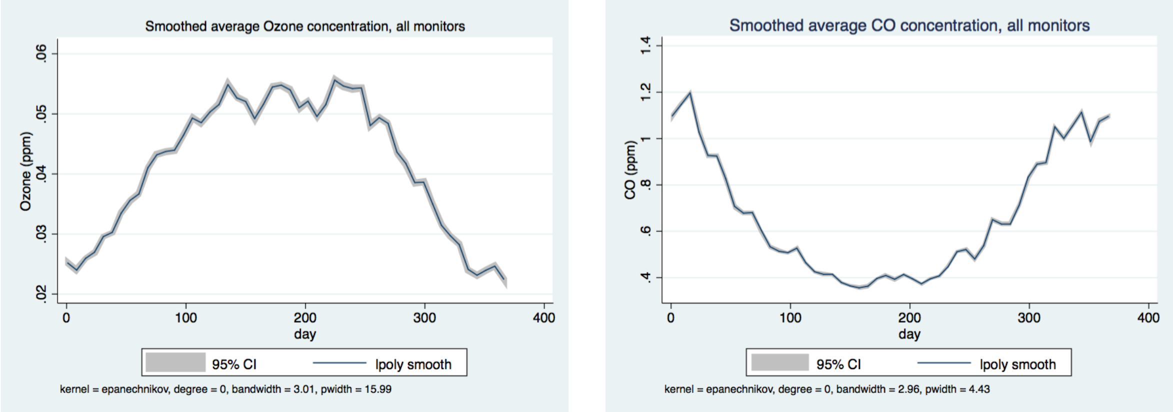

Figure 12: Crime share by hour of day, Chicago

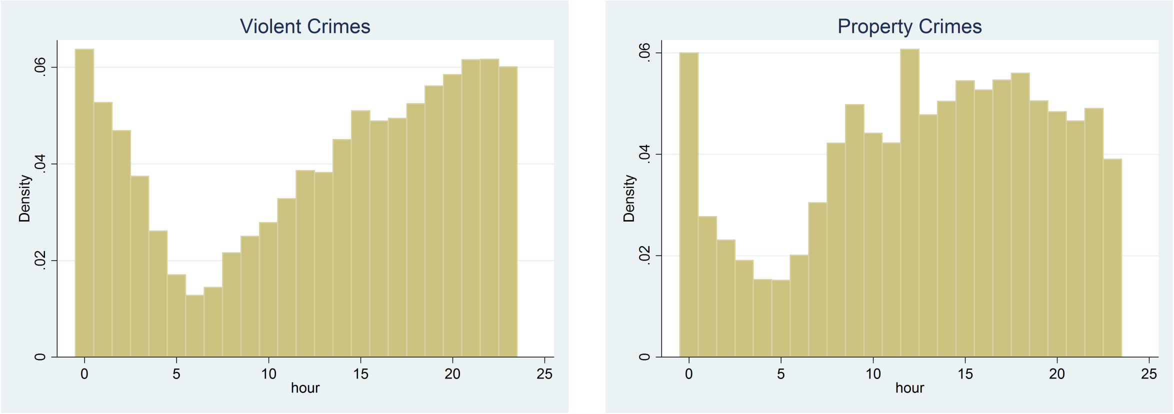

Figure 13: Average crimes by week of year, Chicago

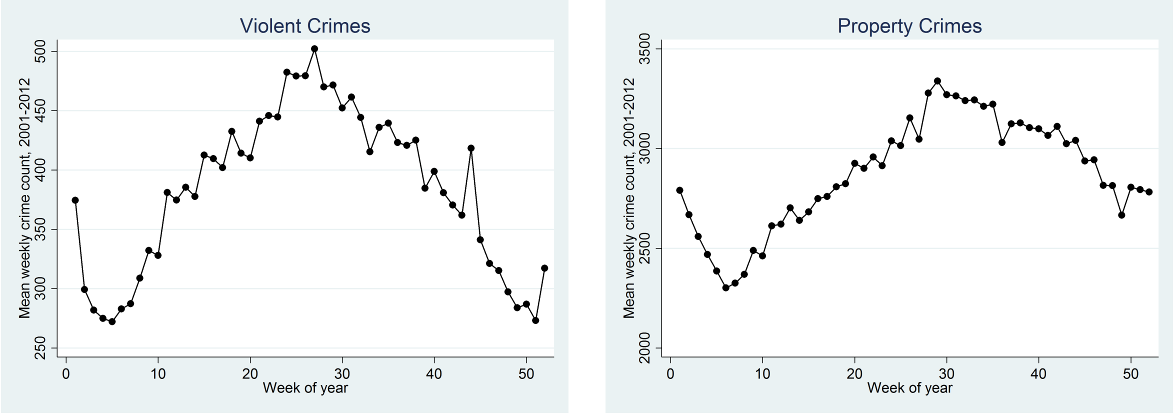

Figure 14: Normalized average annual crimes (2001 levels = 100), Chicago

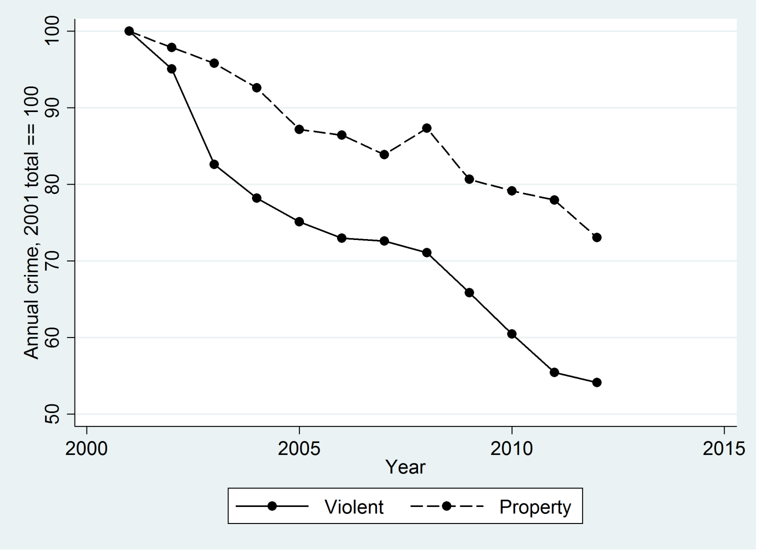

Figure 15: Crime density heat maps, Chicago

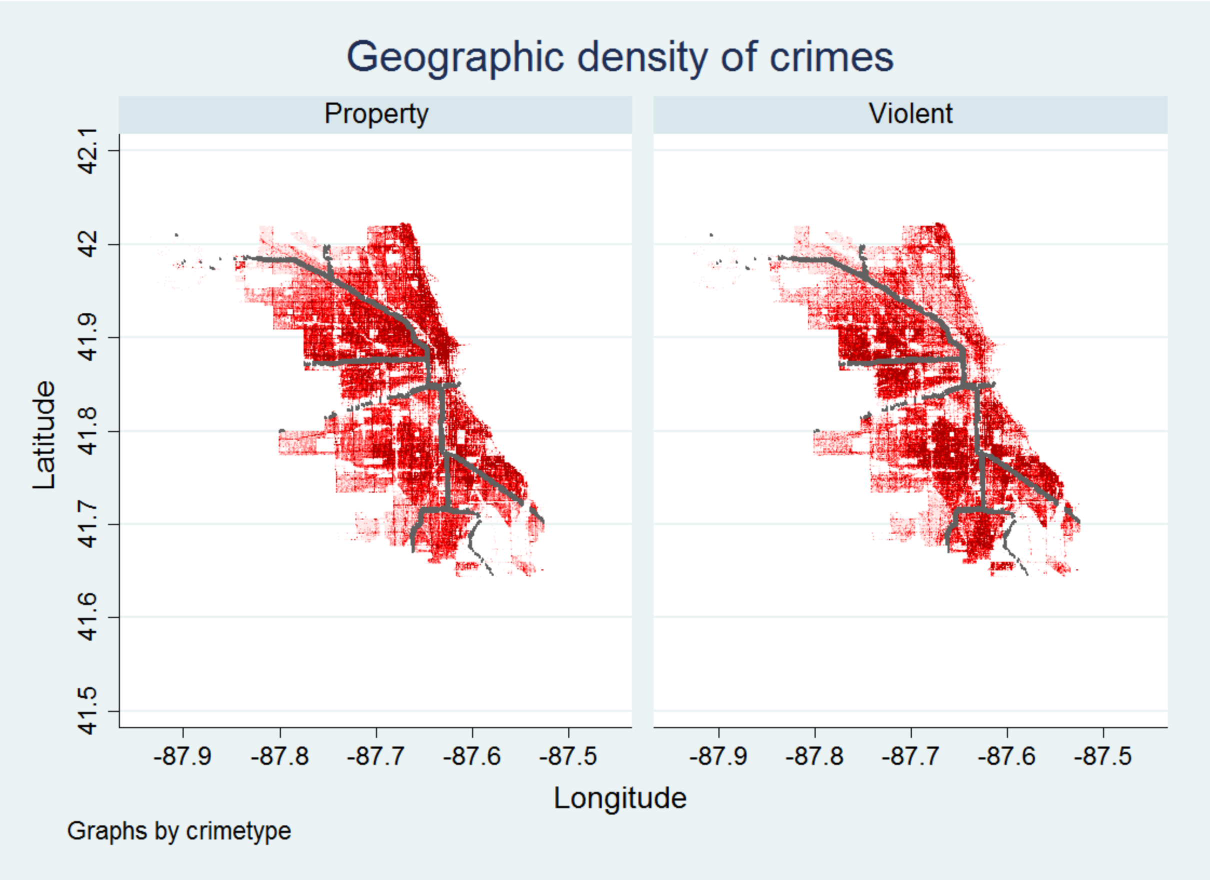

Figure 16: Seasonality in CO and PM10 emissions , Chicago

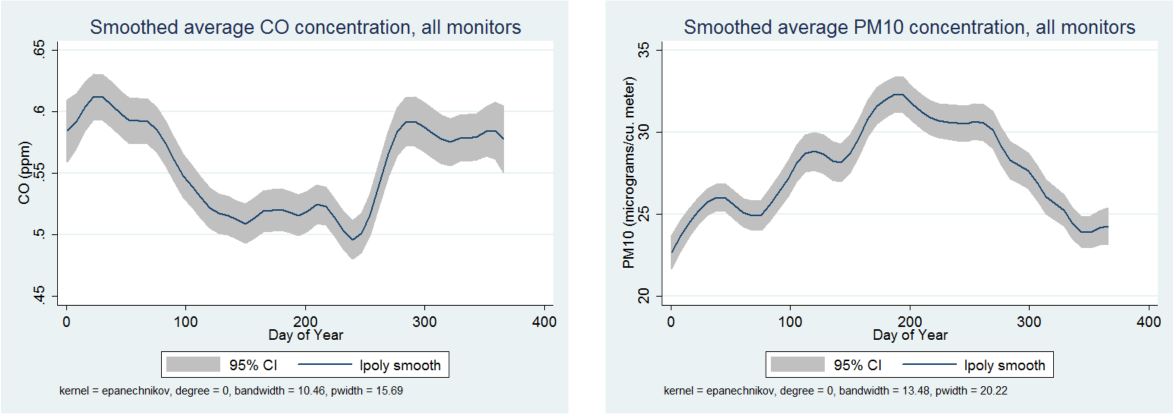

Table 14: LA: Assault, by wind bins

	(1)	(2)	(3)
Treatment*(Wind speed 0 - 2 m/s)	0.175***	0.236***	0.189***
	(0.0336)	(0.0533)	(0.0409)
Treatment*(Wind speed 2 - 4 m/s)	0.158***	0.251***	0.151**
	(0.0419)	(0.0880)	(0.0604)
Treatment*(Wind speed 4 - 6 m/s)	0.184**	0.377**	0.252*
	(0.0834)	(0.165)	(0.129)
Treatment*(Wind speed 6 - 8 m/s)	-0.216	-0.123	-0.159
	(0.138)	(0.198)	(0.159)
Treatment*(Wind speed 8 - 10 m/s)	-0.297	-0.0296	-0.282
	(0.764)	(0.851)	(0.794)
Treatment*(Wind speed 10 - 12 m/s)	-0.864	-0.196	-0.265
	(0.550)	(0.143)	(0.189)
Controls for weather			X
Date FE	X		
AQS FE	X	X	X
Observations	72182	72182	72182
R-Squared	0.748	0.725	0.728

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Dependent variable is daily number of assaults. Standard errors clustered by year-month are in brackets.

Table 15: LA: Assault, by season

	(1)	(2)	(3)
Treatment (West*Location dummy)	-0.108*	-0.128	-0.0120
	(0.0556)	(0.110)	(0.101)
Treatment*Spring	0.261**	0.393*	0.263
	(0.0793)	(0.203)	(0.179)
Treatment*Summer	0.339**	0.454**	0.203
	(0.0846)	(0.210)	(0.156)
Treatment*Autumn	0.296**	0.384*	0.180
	(0.0855)	(0.211)	(0.179)
Main Effects	X		
Controls for weather			X
Date FE	X		
AQS FE	X	X	X
Observations	72182	72182	72182
R-Squared	0.748	0.725	0.728

Notes: *** p<0.01, ** p<0.05, * p<0.1. Reference season in the interaction is winter. Robust standard errors reported. Dependent variable is daily number of assaults. Standard errors clustered by year-month are in brackets.

Table 16: LA: Assault, by weekday/weekend

	(1)	(2)	(3)
Treatment (West*Location dummy)	0.210***	0.582***	0.520***
	(0.0488)	(0.0753)	(0.0553)
Treatment*Weekday	-0.0672	-0.475***	-0.479***
	(0.0563)	(0.0451)	(0.0444)
Main Effects	X		
Controls for weather			X
Date FE	X		
AQS FE	X	X	X
Observations	72182	72182	72182
R-Squared	0.748	0.726	0.729

Notes: *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is daily number of assaults. Standard errors clustered by year-month are in brackets.

Table 17: Chicago: 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 18: Chicago: 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 19: Chicago: 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 20: Chicago: 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 21: Chicago: 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.