Does Pollution Affect Crime? Evidence from U.S. Cities*

Nadezhda V. Baryshnikova† Shannon F. Davidson‡ Dennis Wesselbaum§

University of Adelaide University of Otago University of Otago

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Abstract

In this paper we study the relationship between air pollution and crime. We construct a city-level, hourly data set with 2.4 million crimes and link each crime to data on pollution and controls, e.g. weather variables. We study the effects of four pollutants (nitrogen dioxide, sulphur dioxide, carbon monoxide, and ozone), as these have different neurotoxic effects. Our identification strategy relies on using high dimensional fixed effects and exploiting hourly variations.

We find that carbon monoxide has a positive effect on violent crimes and ozone has a negative effect on property crimes. These relationships are linear and we only find heterogeneity in the effect of ozone on property crimes across cities.

Keywords: Crime, Neurotoxicology, Pollution.

JEL codes: C55, K42, Q53.

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†School of Economics, University of Adelaide, Adelaide, SA 5005. Email: nadezhda.baryshnikova@adelaide.edu.au. Phone: +61 8 8303 4821.

‡Department of Economics, University of Otago, Dunedin, 9054. Email: shannon.davidson@otago.ac.nz.

§Corresponding author. Department of Economics, University of Otago, Dunedin, 9054. Email: dennis.wesselbaum@otago.ac.nz. Phone: +64 3 479 8643.

1 Introduction

This paper investigates the relationship between air pollution and criminal behavior.[1] Air pollution has been identified as a major environmental health problem and a threat to public health (WHO, 2016). Common sources of outdoor air pollution are combustion of fossil fuels as well as industrial and agricultural processes. A rich literature shows that it has effects on morbidity (Currie and Neidell, 2005) and health (Schlenker and Walker, 2016). A growing literature studies the effects of pollution on various other factors including house prices (Chay and Greenstone, 2005), labor supply (Hanna and Oliva, 2015), or cognitive performance (Zhang et al. 2018). We extend the literature on the behavioral effects of air pollution by studying the pollution-crime relationship.

Crime generates large - pecuniary and non-pecuniary - costs for victims and the government. According to the U.S. Government Accountability Office, the annual cost of crime, including intangible costs, was $3.41 trillion in 2017 and the U.S. government (local, state, and federal) paid $280 billion in associated costs, such as law enforcement and judicial processing. Crime prevention is a key goal for public policy and understanding the driving forces of criminal behavior is important to develop prevention strategies and to improve the allocation of resources.

We construct a city-level data set with 2.4 million individual crime observations on an hourly frequency. We select four cities: Chicago, Indianapolis, Los Angeles, and New York City and our data set spans four years: 2014-2017. Each crime is matched to data taken from EPA air quality stations. As we expect pollution to have different effects on types of crime, we categorize crime into violent crime (assault and battery, rape, and homicide) and property crime (larceny, robbery, burglary, and grand theft auto). Our econometric strategy exploits the hourly variation in pollution and crime, controlling for weather variables (temperature, precipitation, humidity, wind speed, and

[1] In this paper, "crime" should be understood as "alleged crime" and all suspects are innocent until proven guilty in a court of law.

wind direction) and a rich set of fixed effects. The mechanisms through which air pollutants affect criminal behavior is taken from two different fields. First, we draw upon research finding that pollutants affect emotions (Evans et al., 1988) and combine this with results showing that emotions are linked to unethical behavior (Gino et al., 2011 and Horberg et al., 2011). Second, the next mechanism is the neurotoxicity of pollutants (Jayaraj et al., 2017 and de Prado Bert et al., 2018). For example, pollutants reduce the level of serotonin in the brain (Vyskocil et al., 1983). In turn, low levels of serotonin are linked to impulsive and aggressive behavior (Seo et al., 2008). These mechanisms work even when humans are exposed to pollutants for a short period of time (Crüts et al., 2008).

Our paper differs in two important ways from the existing literature. First, for the first time, we use hourly observations of crime and air pollution. So far, the literature has relied on daily observations at best (Burkhardt et al., 2019). However, using daily observations to study the weather-crime relationship has been shown to lead to very different conclusions compared to using hourly observations (Baryshnikova et al., 2019). By using hourly observations, we avoid the problem that the daily average hides important within-day variation.

Second, the existing literature uses either the air quality index (Bondy et al., 2018) or the particulate matter (PM) measure (Herrnstadt et al., 2016 and Burkhardt et al., 2019).[2] Both measures average pollutants at any given point in time. The problem is that, as we will discuss later, there is evidence that pollutants differ in their effects on human activity and behavior. Using an average measure hides important variation in the composition of pollution. To avoid this problem and for the first time, we use individual measures for four air pollutants: nitrogen dioxide, sulfur dioxide, carbon monoxide, and ozone. This allows us to perform a more detailed analysis and to

[2] For example, often the $PM_{2.5}$ measure is used, which counts the mass of particles with a diameter of 2.5 micrometers or less.

identify and prioritize the significant pollutants.

Several results stand out. First, carbon monoxide affects violent crime. A higher concentration of carbon monoxide leads to more violent crimes. Second, a higher concentration of ozone reduces property crimes. Both effects are quantitatively important. Nitrogen dioxide and sulfur dioxide do not have significant effects on violent or property crimes. This is in line with the observation that these two air pollutants affect the respiratory system and do not permeate the blood-brain barrier. In a sense, we use these two air pollutants as a placebo test to address concerns about spurious results. Further, besides using the fixed effects regression model, we also provide additional evidence using a machine learning approach. We use 80 percent of our observations as a training sample for two models: a simple model that only includes fixed effects and a model with air pollutants. An out-of-sample prediction on the remaining 20 percent sample shows that the model with air pollutants generates a smaller root-mean-squared error compared to the model with fixed effects only. We take this as further evidence that pollution affects criminal behavior.

We then provide various robustness checks for our key results. Our results are robust to different ways to address concerns about the effect of sunlight (Doleac and Sanders, 2015). Also, we do not find non-linearities in the relationships. Further, we investigate the lag structure of the effect. We find that for carbon monoxide, exposure in the two hours before a crime have a significant effect, while the results for ozone are mixed. We then show that our results also hold when we run our regressions by city: we find almost no heterogeneity in the effect of carbon monoxide on violent crime, but large heterogeneity in the effect of ozone on property crime across cities.

The existing literature on the pollution-crime relationship is small. We are aware of five papers. Rotton and Frey (1985) find more family disturbances have been associated with high levels of ozone. More recently, Herrnstadt et al. (2016) use geocoded crime data and wind direction to account for the variability of pollution in Chicago and Los Angeles to establish a relationship between crime and air pollution ($PM_{2.5}$). Crime data is collected from 2001 to 2012 and 2005 to 2013 for Chicago and Los Angeles, respectively. In Los Angeles the geographical make-up of the city is used as winds concentrate air pollution in pockets within the city. In Chicago the wind direction in relation to an interstate is used to create an area that is treated by air pollution and one that is not. In both cities it is found that air pollution increases violent crime, but does not affect property crime. Bondy et al. (2018) study the link between air pollution (Air Quality Index) and crime in London from 2004 to 2005, using daily crime. The study finds a positive relationship between overall crime and air pollution. Lu et al. (2018) use 9,360 cities in the U.S. over nine years (2001-2009) to study the crime-pollution link. They use city-year variation and find that higher pollution (average over six pollutants) increases crime. They use anxiety as a mechanism that explains this relationship. Finally, Burkhardt et al. (2019) use daily data over nine years on the county level in the United States. They find that higher pollution ($PM_{2.5}$ and daily mean ozone) significantly increase violent crime, but has no significant effect on property crimes.

The rest of the paper is structured as follows. The next section discusses the mechanism through which pollution affects criminal behavior. Section 3 discusses our data and econometric approach. Section 4 discusses our main results, while section 5 discusses various robustness checks. Section 6 briefly concludes.

2 Investigating the Mechanism

In this section we want to discuss how air pollutants could affect human behavior and, therefore, crime. While the exact links between air pollution and crime is not yet fully understood, there are several plausible mechanisms through which a relationship can be explained.

The first plausible mechanism explores the link between pollutants and emotions. Air pollution has been found to increase anxiety (Evans et al., 1988 and Lu et al., 2018) and exposure has been linked to a decrease in tolerance and increase in frustration (Rotton, 1982). Emotions, then, have been linked by various studies to unethical behavior (Gino et al., 2011 and Horberg et al., 2011). Kouchaki and Desai (2015) and Lu et al. (2018) find that anxiety leads to an increase in unethical behavior.

Individual pollutants have been found to cause anxiety and depression. A study conducted on a representative sample of residents in Los Angeles finds that exposure to ozone has a direct link to anxiety, but no link to hostility (Evans et al., 1988). Ozone has also been found to increase oxidative stress in adult rats (Rivas-Arancibia et al., 2010), which has been found to induce anxiety and depressive like behaviours in the same species (Allam et al., 2013 and Patki et al., 2013).

The link between pollutants and anxiety is also found for carbon monoxide (Gale et al., 1999 and Jasper et al., 2005). In Gale et al. (1999), 95 percent of patients experienced affective changes, including depression and anxiety, after exposure to carbon monoxide. In comparison, one study showed no change in emotion when participants were exposed to nitrogen dioxide (Linn et al., 1985).

The second plausible mechanism explores the link between pollutants, the human brain, and behavior. A growing body of research investigates how air pollutants reach (Mumaw et al., 2016 and Elder et al., 2006) and affect the brain.[3] The damage on the brain can be at the cellular and the molecular level (Elder et al., 2006 and Block et al., 2009). The neurotoxicity of air pollutants, according to the literature, is caused by "[...] neuroinflammation, oxidative stress, and/or neurovascular unit dysfunction, which in turn result in oligodendrocytes and/or myelin

[3] For an overview on the link between air pollution and the nervous system see Genc et al. (2011) and for an overview about the neurotoxicity of air pollution see Costa et al. (2017).

damage and loss of neurons or alterations in their morphology." (de Prado Bert et al., 2018).

To be precise, pollutants have been shown to negatively affect white matter in the brain (de Prado Bert et al., 2018). The neurotoxicity of air pollutants is mainly attributed to inflammation and oxidative stress (Jayaraj et al., 2017). These processes affect oligodendrocytes that produce the myelin sheath (main component of white matter) in the central nervous system (Laszkiewicz et al., 1999). Further impacts on impaired synaptic functions (Davis et al., 2013) and neuron death (Ejaz et al., 2014) have been found.

While the literature often documents long-term effects (de Prado Bert et al., 2018), there is also a literature documenting short-term effects. Davis et al. (2013) find that mice exposed to PM for two hours show synaptic dysfunction in the hippocampus. Effects on human's electroencephalograms after a one hour exposure to Diesel exhausts have been documented by Crüts et al. (2008). Araneda et al. (2008) find an effect on glial cells in the central nervous systems of rats who have been exposed to ozone for three hours.

Especially, a channel via serotonin has been documented. Serotonin (5-Hydroxytryptamine) is a primary neurotransmitter, aiding in the transfer of information in the brain and central nervous system. It has been shown that high levels of serotonin go in hand with higher levels of happiness and less mental and physical disorders (Young, 2007). Krueger et al. (1963) find that air quality is a substantial cause of variation in serotonin levels in blood. Furthermore, studies have found that rats exposed to carbon monoxide showed decreased levels of serotonin in the brain (Vyskocil et al., 1983) as well as exposure to ozone has shown similar results (Paz and Huitrón-Reséndiz, 1996, Murphy et al., 2013, and González-Guevara et al., 2014).

Low levels of serotonin have been linked to an increase in impulsive and aggressive behavior (Coccaro et al., 2011 and see Seo et al., 2008 for an overview), and low levels of 5-Hydroxyindolcetic acid (a metabolite of serotonin) in the cerebrospinal fluid has been found in impulsive violent offenders (Linnoila et al., 1983). A depletion of serotonin has also been shown to increase aggression in both women (Daw et al., 2002) and men (Bjork et al., 1999).

The effect of pollution on crime can also be related to existing theories of crime. First, the *Routine Activity Theory* (Cohen and Felson, 1979) emphasizes that three elements are required for a crime to occur, a suitable target, an offender that is motivated, and the absence of a capable guardian to advocate against crime. As shown, air pollutants can affect emotions and can have neurotoxic effects, which can affect the willingness to engage in unethical behavior. In itself, this may increase the motive to commit a crime. Conversely, increased pollution may decrease crime. This relationship can be explained through the *Social Escape/ Avoidance Theory* (Cohn et al., 2004). This model stipulates that one avoids situations that lead to a negative experience. Consequently, increased air pollution may lead to more people staying indoors, reducing social interaction and the likelihood of finding a suitable target.

Second, the *Excitation Transfer/Misattribution of Arousal Model* (Zillimann, 1983) states that the activation of the sympathetic nervous system resulting from excitatory reactions, is largely non-descriptive in terms of the emotion. As a result, a change in pollution resulting in a reaction in the sympathetic nervous system may be misattributed towards an individual, potentially resulting in higher aggression and, therefore, more crimes committed.

3 Data and Methodology

3.1 Variables

Our data set is constructed by combining crime data and pollution data. For the crime data, we collect data on crimes committed between 2014 and 2017 for four cities: New York City, Indianapolis, Chicago, and Los Angeles. For each crime, we collect information on the time (date and time of the crime), nature of the crime (associated penal code), and geo-coding (longitude and latitude). The source of the data is the respective Police Department: New York Police Department, Chicago Police Department, Los Angeles Police Department, and Indianapolis Metropolitan Police Department. We chose those four cities for reasons of data comparability and population size. In several states/cities information on certain types of crime is not publicly available for confidentiality reasons.

Notice that the penal code reported is for the "primary type" of the crime. Further, while we have the time of the crime by the second it is reported, we expect that there is a (random) delay in reporting, i.e. crimes might be reported later compared to when they are committed. However, unless this delay is related to pollution, our estimation is not affected by this noise.

Overall, we have about 2.4 million crimes in our database. We then disaggregate crimes into violent crime (rape, homicide and assault and battery) and property crime (burglary, larceny, robbery and grand theft auto). This follows the findings by, for example, Herrnstadt et al. (2016) showing that the relationship between air pollution and crime differs for violent and property crime.

Data on the specific pollutants are collected from the United States Environmental Protection Agency (EPA). We extract the following pollutants: sulphur dioxide (SO_2, measured in parts per billion), nitrogen dioxide (NO_2, measured in parts per billion), ozone (O_3, measured in parts per million), and carbon monoxide (CO, measured in parts per million). Measures are averages across stations within cities. The local time and date attached to each measurement is also extracted. The next problem is how to link the crime data (by the second) to the pollutant data (by the hour). All readings are matched to the closest hour. For example, 1:15pm becomes 1pm and anything past the half hour is rounded to the next hour.

Sulphur dioxide is a toxic, highly reactive gas that is a precursor of acid rain. The EPA classifies sulphur dioxide as the greatest concern in the family of sulfur oxides and uses it as an indicator for the concentration of other sulfur oxides. Sulphur dioxide is mainly produced in the burning of fossil fuel at industrial facilities and power plants (e.g. generating electricity from coal/oil/gas that contain sulfur). Less important are vehicles burning fuel with a high sulfur content and industrial processes (e.g. extracting metal from ore).

Nitrogen dioxide is a highly reactive gas (above 21.2 degrees Celsius/70.2 degrees Fahrenheit) that belongs to the larger group of nitrogen oxides. As for sulphur dioxide, the EPA uses nitrogen dioxide as an indicator for the group of nitrogen oxides. It is mainly produced in the process of burning fuel (vehicles and power plants). Carbon monoxide is a gas that plays an important role in the process of producing ground-level ozone.

Carbon monoxide is produced in the combustion process; mainly vehicles but also home appliances such as gas heaters and ovens. Ozone in this paper relates to ground-level ozone rather than ozone in the stratosphere. Ground-level ozone is a gas that is also considered to be a greenhouse gas. It is found in the troposphere, the Earth lowest layer and its concentration increases in the distance from sea-level. In contrast to the three previous pollutants, ozone is not emitted into the air, but is a product of a chemical reaction. Precisely, it is generated by an interaction between nitrogen oxides and volatile organic compounds (organic chemicals created, for example, by emissions from vehicles or power/industrial plants) with temperature and sunlight as further input factors. As argued by the EPA, ozone does not only occur on hot days, but can reach high levels even during colder months.

Finally, we control for the effect of various weather variables on crime (Baryshnikova et al., 2019 and Heilmann and Kahn, 2019). Data for temperature (dry bulb temperature, in degrees Celsius), the relative humidity (measured as a percentage), wind speed (measured in miles per hour), wind direction (angular degree), and precipitation (measured in inches) are collected. The measures are taken from the National Oceanic and Atmospheric Administration's National Centers

	Obs.	Mean	Std. Dev.	Min	Max
Crime					
Total	2,385,324	60.90	35.70	1	221
Violent	784,999	37.97	16.82	1	115
Property	1,600,325	72.14	37.10	1	221
Pollution					
Ozone	2,383,563	0.03	0.02	0	0.10
CO	2,320,975	0.28	0.17	0	3.55
NO_2	2,382,317	15.50	9.11	0	96.5
SO_2	2,212,631	0.91	1.27	0	79.9
Weather					
Temperature	2,383,181	15.43	10.01	-26.14	36.66
Precipitation	2,360,190	0.49	0.90	0	22.2
Humidity	2,385,238	58.42	18.95	0	100
Wind Speed	2,316,244	10.23	8.60	0	49
Wind Direction	2,384,080	174.17	85.78	0	360

Table 1: Descriptive Statistics.

for Environmental Information land-based stations and are matched to crime observations in the same way pollutants are.

3.2 Descriptive Statistics

Descriptive statistics of our variables are presented in table 1. Overall, our sample contains roughly 2.4 million crimes. This breaks down to about 780,000 violent crimes and 1.6 mio. property crimes. Violent crimes are made up by 97 percent of assault and battery, while rape and homicide contribute 2 and 0.7 percent respectively. Property crimes are made up as follows: 63 percent are larceny, 17 percent are burglary, 10 percent robbery, and 10 percent grand theft auto. There is little variation across cities and over time in the composition of violent and property crimes.

We are using four different pollutants. Importantly, we notice that the maximum concentration of each pollutant is far away from levels that would endanger life immediately. These levels are: nitrogen dioxide 200,000 ppb, carbon monoxide, 2,500 ppm, sulphur dioxide, 100,000 ppb, and ozone, 5 ppm. Most importantly, we find significant variation in each pollutant.

3.3 Methodology

Our identification relies on using high dimensional fixed effects, i.e. exploiting hourly variation in pollution and crime. Our econometric approach relies on the comparability of cities with themselves over time. We do not find evidence for shifting spatial patterns of crime over the four years in our sample by city. Therefore, this assumptions appears to hold. While often one is concerned with endogeneity (reverse causality) in the estimation, one of the key advantages of our research design is that pollution is plausibly exogenous: it is hard to argue that crime would lead to more pollutants in the air. Further, while our reduced-form approach does not allow us to answer the question how pollutants affect crime, it allows causal inference. This is obtained by the random variations in pollutants within each city over time.

In the following, we use a linear model

$$\log\left(Crime_{i,t}\right) = \alpha + \boldsymbol{\beta} Pollution_{i,t} + \boldsymbol{\gamma} X_{i,t} + \eta_i + \eta_t + \varepsilon_{i,t}, \tag{1}$$

where i denotes cities, t denotes time and α is a constant. The effect of the four pollutants is captured by $\boldsymbol{\beta}$. The vector $X_{i,t}$ captures weather control variables: temperature, precipitation, humidity, wind speed, and wind direction. We control for these potentially confounding factors as the crime-weather literature (e.g. Baryshnikova et al., 2019 and Heilmann and Kahn, 2019) has shown that crime is affected by weather conditions. We include these variables linearly, but also performed a robustness check with squared terms of all weather controls, which leaves our results unaffected. Our unit of observation is the city-hour ($N = 140,160$).

Given that we find certain patterns of crime (e.g. more crimes happen in summer months, most property crimes happen on a Friday), we include a rich set of fixed effects. First, we control for the fact that cities exhibit a different average level of crimes by including city fixed effects, η_i.[4] Second, we include various fixed effects related to time: year, month, day, and hour, which we denote - abusing notation - by η_t. These capture crime patterns as well as other time-varying factors such as economic cycles or demographic change.

Further, we include two other control variables: Federal holidays and hour and day of full moon.[5] Holidays could affect behavior and therefore lead to different number of crimes committed and the lunar cycle, occasionally, has been linked to human behavior (Lieber, 1978).

Notice that we do not control for variables such as income, education, or socio-economic status. The reasons for this are as follows. First, we want to estimate the total effect of pollutants on crime, rather than the partial effect. Second, the aforementioned variables would not change much on the high-frequency of our observations (hour) and, therefore, would likely be absorbed by the rich set of fixed effects. Third, we want to avoid bad control problems (Hsiang et al., 2013). If the control variables are themselves outcome variables, including them will bias the $\boldsymbol{\beta}$ coefficients.

All our regressions include clustered standard errors at the city level. We expect that a clustering problem is caused by a common unobserved random shock at the city level causing all observations with in each city to be correlated. However, due to the small number of clusters (four), we expected that our standard errors are biased (MacKinnon and Webb, 2018) and use a score wild bootstrap correction (Kline and Santos, 2012).

Finally, at the end of this section we want to develop our hypotheses. We expect that carbon monoxide has a positive effect on violent crimes. It affects emotions and the human brain and leads to more aggressive behavior in the laboratory as shown above. The effect of carbon monoxide on property crimes is ambiguous. On the one hand, when carbon monoxide leads to depression

[4] Most crimes in our sample occur in New York City (942,631), Chicago is second (661,574), L.A. is third (601,533), and Indianapolis is last (200,381).

[5] Federal holidays are: Christmas, Independence Day, New Year's, Veterans Day, Martin Luther King Day, Memorial Day, Washington's Birthday, Labor Day, Thanksgiving, and Columbus Day.

and anxiety it might reduce the number of potential targets on the streets, which would reduce property crimes. On the other hand, it leads to more aggressive behavior, which could increase property crimes. For ozone, we do not expect an effect on violent crime because the study by Evans et al. (1988) found that there is no link between ozone and hostile behavior. As ozone can be seen (e.g. smog), we expect a significant effect on property crimes. However, this effect is ambiguous. If people avoid leaving the house because of smog, this will reduce the probability of a successful burglary, but at the same time reduces the number of able guardians on the streets. The latter could increase property crimes (e.g. robbery).

For nitrogen dioxide and sulfur dioxide we do not expect a significant effect on violent or property crimes. In fact, we use the two air pollutants as placebo tests to address concerns about spurious results. We are not aware of a channel through which these two air pollutants would plausibly affect criminal activity.

4 Main Results

In this section, we discuss our estimation results for the effects of pollutants on crime.[6] We begin by using total crime and then look at the effects on violent and property crime.

Table 2 presents our estimation results, using eq. (1), for total crime. Total crime appears to be significantly affected by variations in ozone. We find that higher levels of ozone reduces total crimes. A ten percent increase in ozone (0.003 ppm at the mean) will decrease total crime by 0.52 percent or about 0.5 crimes per hour (at the mean). The other pollutants, carbon monoxide, sulfur dioxide, and carbon monoxide have no statistically significant effect on total crime. Breaking total crime into violent and property crime will allow us to understand the potential mechanisms that explain this finding.

[6] The appendix presents the regression results using daily observations.

	1	2	3	4
NO_2	0.002^{**} (0.037)	0.002^{**} (0.036)	0.001 (0.729)	-0.0004 (0.845)
SO_2		0.002 (0.165)	0.001 (0.708)	0.002 (0.555)
CO			0.11 (0.240)	0.11 (0.253)
Ozone				-1.73^{***} (0.003)
Obs.	2,288,161	2,117,854	2,068,326	2,066,698
R^2_{adj}	0.82	0.83	0.83	0.83

Table 2: Main results. Dependent variable is hourly total crime. All regressions include temperature, precipitation, humidity, wind speed, and wind direction as well as city, year, month, day of week, and hour of day fixed effects. We also control for holidays, hour and day of full moons. Standard errors are computed using a score wild bootstrap method and p-values are shown in parenthesis. Constant not shown. Significance levels: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

Table 3 presents the results for violent crime. Interestingly, we find that for violent crime, carbon monoxide is the only significant variable. Nitrogen dioxide and sulfur dioxide act as placebo tests in this regression to address worries that our regression set-up might yield spurious results. We do not expect them to have an effect on the human brain as they work through the respiratory system (e.g. Chen et al., 2007). Therefore, we do not expect them to significantly affect violent crime (see also Linn et al., 1985) and this is what our estimation finds.

In contrast, higher levels of carbon monoxide in the air will increase violent crime. A ten percent increase in carbon monoxide levels (0.028 ppm at the mean) will increase violent crime by 0.25 percent or about 0.1 violent crimes per hour (at the mean). All other variables are statistically insignificant. To the best of our knowledge, we are the first to document a relationship between the level of carbon monoxide and violent crime. This finding is in line with the previously discussed links between pollutants and behavior. First, pollutants can affect emotions. Carbon monoxide has been found to affect anxiety and depression (Gale et al., 1999 and Jasper et al., 2005) and anxiety has been shown to lead to more unethical behavior (Kouchaki and Desai, 2015 and Lu et al., 2018). Second, the neurotoxicity of pollutants has been documented (de Prado Bert et al.,

	5	6	7	8
NO_2	0.002**	0.002*	0.001	0.001
	(0.038)	(0.057)	(0.609)	(0.612)
SO_2		0.005	0.004	0.005
		(0.378)	(0.432)	(0.352)
CO			0.09**	0.09*
			(0.0496)	(0.052)
Ozone				−0.59
				(0.784)
Obs.	756,336	685,393	664,949	664,648
R^2_{adj}	0.71	0.72	0.72	0.72

Table 3: Main results. Dependent variable is hourly violent crime. All regressions include temperature, precipitation, humidity, wind speed, and wind direction as well as city, year, month, day of week, and hour of day fixed effects. We also control for holidays, hour and day of full moons. Standard errors are computed using a score wild bootstrap method and p-values are shown in parenthesis. Constant not shown. Significance levels: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

2018) and carbon monoxide has been shown to decrease the level of serotonin (Vyskocil et al., 1983) which, in turn, can lead to an increase in impulsive and aggressive behavior (Seo et al., 2008 and Coccaro et al., 2011). Hence, a plausible explanation for our finding is that carbon monoxide changes emotions and creates neurotoxic effects, which lead to impulsive and aggressive behavior manifesting in an increase in violent crime. This explanation also fits theories of crime. First, the *Routine Activity Theory* (Cohen and Felson, 1979) shows that changes in the surroundings affect the determinants of a crime: (i) suitable target, (ii) a motivated offender, and (iii) the absence of a guardian. Second, the *Excitation Transfer/Misattribution of Arousal Model* (Zillimann, 1983) argues that a change in pollution results in a reaction in the sympathetic nervous system that may be misattributed towards an individual, potentially creating more violent crime.

Table 4 presents the results for property crimes. Here, we find the explanation for why total crimes are negatively affected by ozone levels. While ozone does not significantly affect violent crime, it significantly affects property crimes and is also the only air pollutant to do so. We find that higher levels of ozone reduce property crimes. A ten percent increase in ozone levels (0.003

ppm at the mean) will reduce hourly property crimes by 0.68 percent or about 0.5 crimes (at the mean) per hour.

As for the link between carbon monoxide and violent crime, we can explain this finding using various, previously discussed, mechanisms and theories of crime. First, along the line of the pollution-emotion channel, studies have found that ozone affects anxiety but not hostility (Evans et al., 1988). Further, it has been shown that ozone induces anxiety and depressive like behaviors in rats (Allam et al., 2013 and Patki et al., 2013). Second, ozone has shown to decrease serotonin levels (Paz and Huitrón-Reséndiz, 1996, Murphy et al., 2013, and González-Guevara et al., 2014) which is related to more impulsive and aggressive behavior (Coccaro et al., 2011). Combining these mechanisms with the theories of crime can explain this finding. The *Routine Activity Theory* (Cohen and Felson, 1979) argues that a crime requires three components: a target, a motivated offender, and the absence of a guardian. The *Excitation Transfer/Misattribution of Arousal Model* (Zillimann, 1983) postulates that the reaction in the nervous system triggered by pollution is misattributed towards an individual. While carbon monoxide causes more violent crime, ozone appears to have a different effect and works differently. We also have to understand how ozone is created. Ozone is created by an interaction of various components (nitrogen oxides, volatile organic compounds, temperature, and sunlight). In contrast to carbon monoxide, ozone can be often easily recognized (smog). Hence, people might react to ozone differently than they react to (the invisible) carbon monoxide. For example, people might stay indoors when ozone levels are high. Then, this would reduce the availability of empty houses and, therefore, reduce property crimes. Finally, nitrogen dioxide and sulfur dioxide have no significant effect on property crimes. Again, we use those two air pollutants as placebo tests and our expectation is confirmed that both have no effect on criminal activity.

	9	10	11	12
NO_2	0.002^{**}	0.002^{**}	0.001	-0.001
	(0.047)	(0.038)	(0.800)	(0.751)
SO_2		0.0001	-0.0002	0.001
		(0.974)	(0.962)	(0.861)
CO			0.10	0.09
			(0.479)	(0.492)
Ozone				-2.26^{**}
				(0.010)
Obs.	1,531,825	1,432,461	1,403,377	1,402,050
R^2_{adj}	0.83	0.83	0.84	0.84

Table 4: Main results. Dependent variable is hourly property crime. All regressions include temperature, precipitation, humidity, wind speed, and wind direction as well as city, year, month, day of week, and hour of day fixed effects. We also control for holidays, hour and day of full moons. Standard errors are computed using a score wild bootstrap method and p-values are shown in parenthesis. Constant not shown. Significance levels: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

Overall, our results can be summarized as follows. Violent crime is affected by carbon monoxide and property crimes are affected by ozone. Further, the effects are quantitatively important and can be explained by linking theories of crime and the literature on the effects of pollution on human behavior. Since the existing literature uses average measures of pollutants, it is difficult to relate our findings to them. Burkhardt et al. (2019) find that ozone has a positive effect on assault and a negative effect on robbery and no significant effect on property crimes and grand theft auto. Our results are exactly opposite: we find that ozone has no significant effect on violent crime but significantly affects property crimes. The difference could, for example, be explained by using hourly vs. daily observations or the measurement of ozone. Herrnstadt et al. (2016) find that pollution ($PM_{2.5}$) has a significant effect on violent crimes but not on property crimes in Chicago and Los Angeles. Our results differ in that we also find a significant effect of ozone on property crimes. Here, we suspect that the averaging of pollutants lead to different conclusions.

In this section, we have provided evidence for a link between air pollution and human behavior. We have relied on a fixed effects regression model to identify the significant drivers of criminal activity. A different way to show that air pollutants play a significant role is to use a machine learning approach. We use 80 percent of our sample to train two models: (i) a simple model that

	Total Crime	Violent Crime	Property Crime
FE Only	0.3110	0.3471	0.3481
With Pollution	0.3082	0.3456	0.3447

Table 5: Out-of-sample prediction results. Table shows root-mean-squared error (RMSE) using 80 percent of the data as a training sample and 20 percent for the out-of-sample prediction using the model with only fixed effects (FE Only) and the model with pollution.

only includes fixed effects and (ii) a model as specified in equation (1) with air pollutants. We use the obtained models to predict crime and compare it (out-of-sample) to the unused 20 percent sample. Table 5 shows that the root-mean-squared error (RMSE), as a measure for the goodness of fit, is smaller for the model with air pollutants. We interpret this as further evidence that air pollutants affect criminal behavior.

The next section discusses robustness along three main lines: non-linearity, lagged effects, and heterogeneity across cities. One concern with the identification approach is that crime and pollution trend differently across cities. To address this issue we mainly rely on exploring potential heterogeneity across cities (see next section). In addition, we also run regression including city-year fixed effects, which leaves our results unaffected. Further, we also address another potential threat to identification. As shown in Doleac and Sanders (2015), light has an effect on criminal activity. While our rich fixed effect structure should capture this effect, we additionally perform two robustness checks. First, we construct a city-specific night time dummy (varying between summer (March to November) and winter months), which equals one if a crime has been committed after sunset and before sunrise and zero otherwise. Night has a significant, positive effect on property crimes but an insignificant (negative) effect on violent crimes. Second, we change our fixed effects strategy and include hour-month fixed effects. In both specifications our key results, as discussed in this section, hold.

Finally, we want to briefly discuss the effects of our control variables.[7] The only significant

[7] All results are available upon request.

drivers of violent crime are temperature, wind speed, and holidays. Higher temperature ($p<0.05$), as has been shown before (Baryshnikova et al., 2019 and Heilmann and Kahn, 2019), positively affects violent crime. Wind speed, while significant ($p<0.10$), has no quantitatively important effect on violent crime. We also find that there are significantly more violent crimes on holidays ($p<0.05$). This could be explained by more people on the streets, increasing the availability of victims. For property crimes, we find that only temperature ($p<0.10$) and holidays ($p<0.01$) have a significant effect. Higher temperatures lead to more property crimes. Also, we find that on holidays, less property crimes are committed. Potentially, more people stay at home, which reduces the availability of targets. Similarly, more people on the streets increases the presence of guardians, reducing the incentive to commit a crime. Interestingly, we find that precipitation has no significant effect on property crimes. Typically, research (Baryshnikova et al., 2019) finds that more precipitation reduces property crimes. We show that this effect is not present and, potentially, is captured by ozone. Since most studies on the temperature-crime relation do not control for pollution, it could be that the significant effect of precipitation on property crimes, in fact, should be attributed to ozone.

5 Robustness

5.1 Non-Linear Effects

In this section, we want to analyze whether there is a tipping point in the relationship between each air pollutant and crime. Put differently, we are interested in studying potential non-linearities in the pollution-crime relationship. To do so, we choose to include squared terms of the significant air pollutants in our regression model (eq. 1). Table 6 presents the estimation results for violent and property crime.

Variables	Violent	Variables	Property
CO	0.24^{**}	Ozone	-2.61^{*}
	(0.031)		(0.053)
CO^2	-0.12	$Ozone^2$	3.43
	(0.182)		(0.735)
Obs.	731,493	Obs.	1,532,749
R^2_{adj}	0.72	R^2_{adj}	0.83

Table 6: Non-linear effects of the two significant pollutants. Dependent variable is violent and property crime. All regressions include temperature, precipitation, humidity, wind speed, and wind direction as well as city, year, month, day of week, and hour of day fixed effects. We also control for holidays, hour and day of full moons. Standard errors are computed using a score wild bootstrap method and p-values are shown in parenthesis. Constant not shown. Significance levels: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

We find that for the carbon monoxide-violent crime relation as well as for the ozone-property crime relation there is a linear relationship but not a non-linear relation, i.e. squared terms are insignificant. The only related finding is by Burkhardt et al. (2019) finding an inverted U-shaped response of violent crime in ozone. Our findings imply that there are no tipping points (or thresholds) at which behavior changes. For carbon monoxide, as it is not possible to detect it, this is less surprising as the finding for ozone.

5.2 Lagged Effects

So far, we have considered the contemporaneous effects of pollutants on crime. In the following, we want to consider that the effects of pollutants build-up and affect behavior with a lag. Similar to Burkhardt et al. (2019) and Herrnstadt et al. (2016) we, therefore, include the lagged values of pollutants in our regressions. Table 7 presents the estimation results for the two significant relationships: carbon monoxide-violent crime and ozone-property crime. The table shows the effect of the following lags: one hour, two hours, three hours, six hours, twelve hours, and 24 hours.

For violent crime, we find that the one and the two hour lags are significant. As for the contemporaneous effect, both lags have a positive effect on violent crime. We take this as evidence that behavior is affected by immediate environmental factors rather than a slow build-up of shocks. This finding is in line with laboratory studies such as Araneda et al. (2008), Crüts et al. (2008), and Davis et al. (2013). For property crimes, the lag structure is more complicated. We find a significant contemporaneous effect and the one hour lag is significant. Both have the already discussed negative effect on property crimes. In addition, we also find that the six hour lag has a positive, significant effect and the 24 hour lag has a negative, significant effect. The latter could be explained by persistence of behavior over time. If people stay home yesterday, that might affect the probability of staying at home today. The former could be explained by a catching-up effect. If ozone six hours ago was high and people stayed at home, they might - six hours later - have to go outside, for example, for grocery shopping or picking kids up from school. This would increase the availability of targets and could increase crime.

Finally, in a general sense our results are in line with the findings by Burkhardt et al. (2019) and Herrnstadt et al. (2016) who find that pollution on previous days (as they use daily data) has significant effects on crimes today.

5.3 Heterogeneity across Cities

In this section, we want to address the potential heterogeneity in the effect of air pollutants across cities. To address this issue, we run our estimation for each city individually. Table 8 presents the results for violent crime and table 9 presents the results for property crimes for the four cities in our sample. We again estimate the model defined by eq. (1), but, of course, without city fixed effects. We also now cluster standard errors at the year level and again correct using a wild bootstrap procedure.

For violent crimes, we find that the effect is almost identical across cities. Hence, there is no

Variables	Violent	Variables	Property
CO	-0.03 (0.551)	Ozone	-1.36^{*} (0.061)
CO (-1)	0.13^{**} (0.031)	Ozone (-1)	-0.84^{*} (0.057)
CO (-2)	0.08^{*} (0.066)	Ozone (-2)	-0.09 (0.669)
CO (-3)	-0.02 (0.799)	Ozone (-3)	-0.42 (0.321)
CO (-6)	-0.02 (0.266)	Ozone (-6)	1.80^{*} (0.076)
CO (-12)	0.07 (0.456)	Ozone (-12)	0.51 (0.708)
CO (-24)	-0.04 (0.224)	Ozone (-24)	-1.16^{***} (0.001)
Obs.	720,480	Obs.	1,527,974
R^2_{adj}	0.72	R^2_{adj}	0.83

Table 7: Hourly lags of the two significant pollutants. Dependent variable is violent and property crime. All regressions include temperature, precipitation, humidity, wind speed, and wind direction as well as city, year, month, day of week, and hour of day fixed effects. We also control for holidays, hour and day of full moons. Standard errors are computed using a score wild bootstrap method and p-values are shown in parenthesis. Constant not shown. Significance levels: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

	New York City	Chicago	Los Angeles	Indianapolis
CO	0.09^{**} (0.045)	0.10^{**} (0.022)	0.08^{***} (0.009)	0.09^{*} (0.070)
Obs.	272,780	247,110	184,661	26,942
R^2_{adj}	0.51	0.54	0.57	0.27

Table 8: Robustness. Effects of pollution on violent crime across cities. All regressions include temperature, precipitation, humidity, wind speed, and wind direction as well as city, year, month, day of week, and hour of day fixed effects. We also control for holidays, hour and day of full moons. Standard errors are computed using a score wild bootstrap method and p-values are shown in parenthesis. Constant not shown. Significance levels: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

heterogeneity in the effect of carbon monoxide on violent crimes. Since it is not possible to detect carbon monoxide without a detector and our mechanisms (emotions and neurotoxicology) should not vary across cities, this finding is not unexpected. The finding that pollution affects violent crime in Los Angeles and Chicago is in line with the finding by Herrnstadt et al. (2016) showing that $PM_{2.5}$ has a significant effect on violent crimes in both cities.

Our results are different for ozone. Here, we find that the effect does vary sizably across cities. The smallest effect is found in Los Angeles and the largest in Chicago, with New York City and Indianapolis relatively close to each other. While the effects of ozone on the human body should be the same across cities, ozone, in contrast to carbon monoxide, can be detected. For example,

	New York City	Chicago	Los Angeles	Indianapolis
Ozone	-1.19^{***}	-2.39^{***}	-0.81^{**}	-1.38^{**}
	(0.005)	(0.006)	(0.041)	(0.020)
Obs.	590,339	378,335	407,095	156.980
R^2_{adj}	0.79	0.69	0.78	0.61

Table 9: Robustness. Effects of pollution on property crime across cities. All regressions include temperature, precipitation, humidity, wind speed, and wind direction as well as city, year, month, day of week, and hour of day fixed effects. We also control for holidays, hour and day of full moons. Standard errors are computed using a score wild bootstrap method and p-values are shown in parenthesis. Constant not shown. Significance levels: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

smog can be seen. Therefore, the reaction of people to visible ozone in the air could be stronger in Chicago compared to Los Angeles. If, for the same concentration of ozone, more people change their behavior (e.g. stay at home) in Chicago, it is possible that this will have a larger effect on crime, compared to Los Angeles. This finding contrasts the Herrnstadt et al. (2016) finding that $PM_{2.5}$ has no significant effect on property crimes in Chicago and Los Angeles. This difference supports our disaggregate approach to measuring the effect of pollutants on crime.

6 Conclusion

In this paper, we study the relationship between air pollution and crime. We construct a city-level data set with 2.4 million individual crime observations on an hourly frequency. We combine this crime data with data on four air pollutants and other control variables (weather variables, full moon, and holidays). Our econometric strategy exploits the hourly variation in pollution and crime and high dimensional fixed effects. The mechanism through which air pollutants affect criminal behavior is taken from research on emotions and crime (Evans et al., 1988 and Horberg et al., 2011) and neurotoxicity of pollutants (Jayaraj et al., 2017 and de Prado Bert et al., 2018).

Our key findings can be summarized as follows. Carbon monoxide has a positive relation to violent crimes and ozone has a negative relation with property crimes. These relationships are linear and only the immediate pollution concentration (lags of one or two hours) is relevant. Carbon monoxide has similar effects across cities, while ozone has different effect across cities.

Our study faces two potential limitations. First, a concern could be the endogeneity of policing. If police departments react to pollution, then our findings might be related to more or less police officers on the streets rather than direct effects of pollutants. However, we are not aware of any (anecdotal) evidence that police departments would react to pollution concentration. Second, our study spatially averages pollutants within cities. Doing so removes potentially interesting within-city spatial variations. Again, as we do not find evidence that the spatial patterns of crime change over time, we do not expect this to be a problem in our econometric strategy. In addition, using the spatial dimension of the data would also run into selection problems. We leave this to a follow-up project. Finally, our observation that precipitation has no significant effect on property crimes opens the question whether the established relationships in the weather-crime relation are robust to controlling for pollutants. Our findings indicate that instead of precipitation, it is ozone that affects property crimes. We believe that the weather-pollution-crime relation deserves more attention.

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7 Appendix

	Violent	Property
NO_2	-0.0003	-0.001
	(0.67)	(0.49)
SO_2	0.006	0.005^{*}
	(0.21)	(0.095)
CO	0.06^{**}	0.03
	(0.03)	(0.72)
Ozone	-0.63^{**}	-0.66
	(0.03)	(0.36)
Obs.	664,648	1,402,050
R^2_{adj}	0.93	0.93

Table 10: Robustness. Dependent variables are daily violent and property crime. All regressions include temperature, precipitation, humidity, wind speed, and wind direction as well as city, year, month, day of week, and hour of day fixed effects. We also control for holidays, hour and day of full moons. Standard errors are computed using a score wild bootstrap method and p-values are shown in parenthesis. Constant not shown. Significance levels: ***: p < 0.01, **: p < 0.05, *: p < 0.10.