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IZA DP No. 11492

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ABSTRACT

Crime is in the Air: The Contemporaneous Relationship between Air Pollution and Crime*

Many empirical studies have examined various determinants of crime. However, the link between crime and air pollution has been surprisingly overlooked despite several potential pathways. In this paper, we study whether exposure to ambient air pollution affects crime by using daily administrative data for the years 2004-05 in London. For identification, we mainly rely on the panel structure of the data to estimate models with ward fixed effects. We complement our main analysis with an instrumental variable approach where we use wind direction as an exogenous shock to local air pollution concentrations. We find that elevated levels of air pollution have a positive and statistically significant impact on overall crime and that the effect is stronger for types of crime which tend to be less severe. We formally explore the underlying mechanism for our finding and conclude that the effect of air pollution on crime is likely mediated by higher discounting of future punishment. Importantly, we also find that these effects are present at levels which are well below current regulatory standards and that the effect of air pollution on crime appears to be unevenly distributed across the income distribution. Overall, our results suggest that reducing air pollution in urban areas may be a cost effective measure to reduce crime.

JEL Classification: H23, K42, Q53

Keywords: air pollution, crime, economic incentives

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I. Introduction

Over the past few decades, crime has been a major policy issue in both national and local politics due to its significant social and economic cost. According to an official government report, the total cost of crime in England and Wales is approximately £60 billion per year[1]. This figure, which is far from comprehensive, suggests that effective crime reduction measures have the potential to provide substantial savings. Indeed, a large body of literature studying the determinants of crime has offered several potential measures to tackle crime such as increased police presence and better education (Draca et al., 2011; Machin et al., 2011)[2]. However, the link between improved air quality and crime reduction has been surprisingly overlooked in the empirical literature despite several potential pathways.

In this paper, we study whether short-term exposure to elevated levels of ambient air pollution affects crime in London. We believe that London provides an almost ideal setting for this type of study for two main reasons. First, the high quality of the daily administrative crime data, in conjunction with the extensive network of air pollution monitoring stations, allows us to overcome the many identification problems, such as measurement error and the presence of unobserved correlated factors. Second, London is similar to many major cities around the world in terms of its characteristics. According to the 2017 Economist Safe Cities Index and recent figures from the World Bank, both pollution and safety levels in London are almost identical to other major cities such as Chicago and New York[3]. Therefore, our results should be of

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[1] This figure is taken from the Home Office Research Study 217 which was published in 2000. In 2005, the Home Office revised the estimates for the total cost of crime against individual and households to about £36.2 billion per year but this figure does not include crimes against business and the public sector.

[2] Policymakers also tend to focus on these measures. For example, the mayor of London recently claimed that real-terms cuts in various public services such as community education and the police had "reversed decades of progress in tackling the root causes of violent offending" (The Independent, 2018).

[3] The 2017 Economist Safe Cities Index, which ranks 60 major cities around the globe, placed London in the 20th spot for overall safety (between Chicago (19) and New York (21)). The pollution data is for PM10.

particular interest to policymakers not just in London, but also to those in many other large cities around the world.

We estimate the effect of air pollution on crime using a unique data set, which combines readings of ambient air pollution concentrations with rich administrative records on over 1.8 million criminal offences recorded in London during the years 2004-2005. To account for potential confounders we take the following measures. First, we rely on the panel structure of the data to estimate models with ward fixed effects. Second, we complement our main analysis with an instrumental variable approach, where we use wind direction as an exogenous shock to local air pollution concentrations. Finally, we perform a range of robustness and placebo tests, which provide additional support to the causal interpretation of our analysis.

The results suggest that exposure to elevated levels of air pollution is associated with increased crime rates. In our preferred fixed effects specification we find that an additional 10 Air Quality Index (AQI) points increase the crime rate by 0.9% and experiencing an AQI of above 35 leads to 2.8% more crimes. The latter result, which is equivalent to 0.07 of a standard deviation, is very large and similar to the estimated effect of a 9% decrease in police activity (Draca et al., 2011)[4]. Our instrumental variable approach, which uses wind direction as an instrument that can flexibly influence pollution at different locations, yields statistically similar results. More specifically, we find that additional 10-instrumented AQI points increase crime rate by 1.7%. Finally, we explore whether ambient air pollution has heterogeneous effects on crime types and across the income distribution. We find that the effect is stronger for types of crime which tend to be less severe and that the effect appears to be unevenly distributed across resident income groups.

[4] Draca et al. (2011) focus on the effect of increased police presence following the July 2006 terror attacks in London.

To explain the underlying mechanism for our findings, we complement our empirical results with a formal economic framework rooted in the rational choice theory of crime (Becker, 1968). In the context of this framework, we expect short-term fluctuations in air pollution to influence criminal activity through any of the following three channels – (i) altering perceived payoffs, (ii) altering risk perceptions, or (iii) altering risk preferences. Based on our empirical results we conclude that the effect of air pollution on crime is likely mediated by higher discounting of future punishment.

Overall, this study provides several important contributions to the literature on crime, as well as carrying important implications for public policy more broadly. First, our results suggest that improving air quality in urban areas may provide a cost effective way to reduce crime. Second, the link between pollution and crime suggests that the optimal deployment of law enforcement resources (e.g. local police personnel) should incorporate information from pollution forecasts. Third, our results are present at levels which are well below current US Environmental Protection Agency (EPA) and UK Department for Environment, Food & Rural Affairs (DEFRA) standards which suggests that it may be economically beneficial to lower existing guidelines. Finally, this study also contributes to the evolving body of research studying the link between ambient pollution and the impact on other aspects of human life such as productivity, cognitive performance and sports performance (Graff-Zivin and Neidell, 2012; Ebenstein et al., 2016; Lichter et al., 2017). More specifically, given the link between air pollution and crime, our results therefore suggest that examining the effects of air pollution on health impacts alone may lead to a substantial underestimation of its societal costs.

II. Background and Conceptual Framework

a. The Adverse Effects of Air Pollution on Human Life

The adverse health effects of ambient air pollution are well-established in the epidemiology and economic literature. Early epidemiological studies documented a strong association between extreme pollution events, such as the London Great Smog, and mortality (Logan, 1953). Later studies, which evaluate the link between pollution and health with lower and more common air pollution levels, found that ambient pollution affects life expectancy and hospitalisation (Dockery et al., 1993; Pope et al. 1995). The economic literature, which better accounts for potential confounders, has also documented a strong link between air pollution and various health outcomes such as infant mortality and emergency room visits (Chay and Greenstone, 2003; Schlenker and Walker, 2015). More recently, a new wave of studies has examined the impact of pollution on other aspects of human life. For example, Graff Zivin and Neidell (2012) presented robust evidence for a causal link between ozone and productivity of agricultural workers in California; Ebenstein et al. (2016) found that elevated levels of $PM_{2.5}$ reduce student test scores among Israeli students; Sager (2016) documented a robust causal relationship between pollution and road safety in the UK; and Lichter et al. (2017) showed that variation in pollution affects professional soccer players in Germany.

Despite this growing body of literature on the adverse effects of air pollution on many aspects of human life, the evidence on the link between pollution and crime is extremely scarce[5]. To the best of our knowledge there are only three papers in the economic literature which examine somewhat related links. The first two papers (Reyes, 2007; 2015) examine the link between childhood lead exposure and crime rates later in life in the United States. The

[5] There are a few studies that examine the effect of other environmental factors, such as temperature, on crime. For example, a number of studies find a significant association between temperature and violent as well as property crimes (e.g. Ranson, 2014; Cohen and Gonzalez, 2018). A recent review of the literature on climate and conflict is provided by Burke et al. (2015).

first paper uses state-year panel data to examine within state variation in lead exposure and crime. The results suggest that lead exposure during childhood is associated with violent crimes but not with property crimes. The second paper also finds a link between early childhood lead exposure and criminal behaviour, using data on two cohorts of children from the NLSY. Finally, a working paper by Herrnstadt et al. (2016) examines the contemperenous link between pollution and crime in Los Angeles and Chicago. Similar to several other studies on air pollution (Anderson, 2015; Deryugina et al., 2016), they also use daily wind direction as an instrument for ambient air pollution. More specifically, they compare relative criminal activity on opposite sides of major interstates in Chicago, on days when the wind blows orthogonally to the direction of the interstate. In LA, they compare crimes in communities on the foothills of the San Gabriel Mountains with those in other parts, on days with and without winds blowing from the ocean towards this region[6]. Overall, they find that violent crime in Chicago increase by 2.2% per day on the downwind side of the interstate with no effect on property crime. In Los Angeles, they find a 19.4% increase in assaults for a 10ppb increase in ozone exposure. Their paper is the closest one to our study but there are several important differences between the two. Most notably, whilst they remain agnostic regarding the underlying mechanisms, we investigate the influence of pollution on crime within a rational choice framework. By combining our theoretical framework with our empirical evidence, we are able to provide strong evidence that pollution raises crime rates through a change in the cost-benefit trade-off. Furthermore, we analysed a wide range of crime types and find that pollution affects not only violent, interpersonal crime (which is the focus of their paper), but also a range of other crimes including those that are more economically motivated. Finally, we also provide some

[6] The logic here is that the San Gabriel Mountains trap the pollution in communities on its foothills during these days.

evidence regarding the distributional aspects, where we analyse the relationship between air pollution and crime across resident income groups.

b. Conceptual Framework: Pollution and Crime

To better understand the mechanism for the potential link between pollution and crime we embed our analysis in the canonical rational choice model of crime proposed by Becker (1968) and Ehrlich (1973), which characterises the supply of criminal activity as driven by individual decision making under risk[7]. Following Becker (1968), a potential offender j chooses to commit an offence if her expected utility from the crime outweighs the utility of a certain outside option, so if:

$$p_j\, U_j\big(W_j^c - \beta S_j^c\big) + \big(1 - p_j\big)U_j\big(W_j^c\big) > U_j\big(W_j^{nc}\big)$$

Given a fixed outside option W_j^{nc} [8], any potential offender j is more likely to commit an offence if: (i) the payoff from crime W_j^c increases relative to the cost of future punishment S_j^c which is discounted at the rate β, (ii) the probability of being punished p_j is lowered, or (iii) the potential offender's preferences $U_j(.)$ become more risk accepting[9] [10].

As outlined above, exposure to air pollution has been linked to changes in behaviour, productivity and well-being. In the context of the rational choice framework, we may expect short-term fluctuations in air pollution to influence criminal activity through any of the

[7] We choose rational choice as our guiding framework in understanding the relationship between acute exposure to air pollution and criminal activity. Rational choice is only one of many frameworks to understand criminal behaviour. Other prominent theories focus for example on persistent personality traits (e.g. Nagin & Paternoster, 1993) or social structure (Saw & McKay, 1942; Bursik, 1988) – with both of these examples less applicable for the short-term (daily) fluctuations in crime that are the subject of our analysis.

[8] A large share of the economics of crime literature focuses on longer term determinants of crime, so that W_j^{nc} might for example correspond to earnings from legitimate work. In our framework, which focuses on short-term decisions, W_j^{nc} may reflect factors shaping the utility of refraining from committing an offence on that given day.

[9] There is indeed robust evidence that the expected gain as well as the likelihood and magnitude of punishment do influence the supply of offences in the expected direction. Most recently, Draca et al. (2018) find substantial responses of property crimes to commodity prices in the United Kingdom for the years 2002-2012.

[10] Alternatively, we can use a more common additive time separable formulation as follow:

$$U_j\big(W_j^{0,c}\big) + \beta\left[p_j\, U_j\big(W_j^1 - S_j^c\big) + \big(1 - p_j\big)U_j\big(W_j^1\big)\right] > U_j\big(W_j^{0,nc}\big) + \beta\, U_j\big(W_j^1\big)$$

following three channels − (i) altering perceived payoffs (W_j^c and βS_j^c), (ii) altering risk perceptions (p_j), or (iii) altering risk preferences ($U_j(.)$). In principle, a potential influence of air pollution may then either increase or decrease criminal activity. For example, if elevated levels of air pollution lead to increased risk aversion, we would expect to see a decrease in criminal activity on high polluted days. Conversely, if air pollution reduces expected cost of future punishment, via lower discounting (β) for example, we would expect to observe increase in crime on days with pollution. We will discuss evidence for each of these possible channels with our results below.

III. Data

Our final data set combines several files which contain administrative information on crime rates, ambient air pollution, weather and various demographics. For crime information, we use data from the London Metropolitan Police Service which contains ward level detailed daily police reports of all recorded crimes in the Greater London area for the years 2004-2005[11]. Importantly, the data allows us to know not just the number of crimes per ward per day, but also the type of crime. Furthermore, the file also provides data on police deployment, tube journeys and unemployment levels which were originally obtained and defined as follow. Data on police deployment was taken from the police service's human resource management system and contains the total weekly number of hours worked by officers for each of the 32 boroughs in London. The weekly data on total number of tube journeys was taken from Transport for London (TFL) and information on borough's unemployment levels were taken from the UK Quarterly Labour Force Survey (LFS)[12].

[11] This data file is taken from Draca et al. (2011). The file does not include data on the City of London, which is one of the 33 local authority districts of Greater London.
[12] In our analysis we divided the weekly total number of tube journeys in each borough by the number of tube stations in the same borough.

For information on pollution and weather, we use daily data from the Department for Environment Food and Rural Affairs (DEFRA, 2017) and the Met office (2012). These files provide information on daily means of five pollutants, temperature, relative humidity, rainfall and wind direction and speed from 96 monitoring stations in the London area (see figure 1). In our analysis we use the AQI, which is calculated according to the US EPA formula, as our main pollution measure. More specifically, we define the overall daily AQI as the highest AQI among the individual pollutants, which is in line with the EPA reporting guidelines.

We assign pollution and weather to wards by linking it with the three monitoring stations closest to the ward centroid. We then use the mean value of those three measurements weighted by the inverse squared distance between station and ward. We also attempted alternative approaches of assignment and the results are nearly identical. Finally, we add population data from London's Ward Atlas (2017) and data on house prices by ward from the Land Registry (2017) to test whether the effect of pollution on crime varies across the resident income groups[13].

Table 1 presents summary statistics for our key variables of interest. Our sample includes 455,520 observations of daily crime counts (over 1.8 million criminal offences in total) across 624 wards in London[14]. The average daily AQI and the number of crimes per 100,000 people during our sample period were 30.06 and 34.06 respectively. Figure 2 plots the distributions of AQI and total number of crimes in our sample. In columns (2)-(3) of Table 1 we stratify the sample by the median house price. As expected, we don't find meaningful differences in temperature, relative humidity and rainfall. However, the table indicates that

[13] The alternative approaches are (1) using only the reading from the station closest to each ward (2) using the closest valid reading from the three closest stations.

[14] The day of the July 2005 attack is dropped from the sample (reducing it to 730 days) leaving a sample of 730*624=455,520 observations.

both, pollution levels and the number of crimes, are higher in wards where house prices are above the median.

IV. Empirical Strategy

There are several identification challenges for inferring a causal link between pollution and crime. The prime concern is the possible presence of unobserved correlated factors. For example, if pollution is higher in poorer areas, a naïve OLS estimate might overstate the effect of pollution on crime, as crime may be higher in those areas for other correlated reasons (e.g. lower quality of education). We overcome this and other related econometric challenges by using two separate identification strategies as follow.

a. Panel Fixed Effects Model:

In our first empirical approach, we crucially rely on the panel structure of the data to estimate models with ward fixed effects. More formally, we estimate models of the following form:

$$Ln(Crime_{it}) = \beta AQI_{it} + f(Temp_{it}, RH_{it}) + \tau Wind_{it} + \omega Rain_{it} + \boldsymbol{C}_{it}\Pi + \boldsymbol{\mu}_t + \gamma_i + \varepsilon_{it}$$

Where, $Ln(Crime_{it})$ is the log of crime in ward i on day t and AQI_{it} is the corresponding air quality index. We control for weather conditions through $f(Temp_{it}, RH_{it})$, which is a flexible function of mean temperature and relative humidity[15], as well as local measures of wind speed ($Wind_{it}$) and total precipitation ($Rain_{it}$). $\boldsymbol{C}_{it}$ is a vector of local area controls accounting for time-

[15] We control for a flexible influence of temperature and humidity by including: dummy variables for 5 temperature bins of equal size, RH_{it}, $(RH_{it})^2$, $Temp_{it} \cdot RH_{it}$, and $(Temp_{it} \cdot RH_{it})^2$.

varying conditions potentially related to pollution and crime[16]. $\boldsymbol{\mu_t}$ and γ_i are time and ward fixed effects respectively. Finally, ε_{it} is an idiosyncratic error term.

Through the inclusion of ward fixed effects our identification relies on the comparison of crime levels between days with higher and days with lower pollution levels within the same ward. This approach removes any potential confounding from time-invariant structural differences between wards, which as mentioned above, is a prime concern.

Weather controls are included because of well documented evidence which show that weather conditions can influence both pollution levels (Zannetti, 2013) and criminal activity (Burke et al., 2015; Cohen & Gonzalez, 2018). We also include further control variables intended to account for time-varying local conditions that may influence criminal activity. Tube activity acts as a proxy for general levels of activity and crowdedness, which may again influence both pollution and crime. Unemployment rates and the level of police deployment serve as additional controls for potentially confounding factors. It is conceivable that more police officers being deployed influences both pollution and crime. Similarly, we may hypothesise that short-term fluctuations in unemployment are associated with both levels of pollution and crime[17].

A final concern may be periodic co-movement between pollution and crime unrelated to the causal effect hypothesised above. For example, we may expect busy weekdays to differ from quiet Sundays both in pollution levels and criminal activity. To account for such systematic time-varying factors, we include in $\boldsymbol{\mu}_t$ a collection of time fixed effects. These include dummies for the Day of the Week to counter the potential short-run seasonality

[16] We rely here on the following control variables from the data compiled by Draca et al. (2011): borough-level unemployment rate, the number of tube journeys (separately measured for weekdays and the weekend), and the (natural logarithm of) total hours of police deployment. These characteristics vary by week.

[17] As these variables may also be seen as outcomes of the treatment ('bad controls') we also analysed the data without including them as controls. The resulting estimates were very similar although slightly higher. We decided to take a conservative approach and keep them in our final specification, as this specification yield slightly lower estimates.

problem described above. We also introduce 24 year-month dummies intended to account for any larger seasonal co-movement as well as time trends. Finally, we include dummies accounting for the six week period of intensified police presence following the July 2005 terror attack, both in London as a whole and in special focus areas identified by Draca et al. (2011) to have had an influence on criminal activity.

b. Instrumental Variable Model:

We believe that our fixed effect strategy in conjunction with the range of control variables yields credible estimates of the effect of air pollution on crime. However, since air pollution levels are not randomly assigned, we cannot conclusively rule out the presence of unobserved time varying correlated factors. Furthermore, the above model may be susceptible to reverse causality and measurement error which may also bias our results[18]. We therefore complement our main empirical strategy with an instrumental variable approach which relies on changes in wind direction as exogenous shocks to local air pollution concentrations. More formally, we estimate the following model:

$$AQI_{it} = \boldsymbol{\rho_i WindDir_{it}} + \delta(Temp_{it}, RH_{it}) + \phi Wind_{it} + \varphi Rain_{it} + \boldsymbol{C}_{it}\kappa + \boldsymbol{\eta_t} + \theta_i + v_{it} \quad (1)$$

$$Ln(Crime_{it}) = \alpha \widehat{AQI_{it}} + f(Temp_{it}, RH_{it}) + \tau Wind_{it} + \omega Rain_{it} + \boldsymbol{C}_{it}\Pi + \boldsymbol{\mu_t} + \gamma_i + \varepsilon_{it}(2).$$

Ln(*Crime*$_{it}$) is again the log offence count in ward i on day t and AQI_{it} the corresponding pollution level. We rely on hourly observation on the principal direction of wind, which we aggregate into the share of hours in the 24-hour period in which wind blows from one of four

[18] A reverse causality is conceivable if more crime causes more pollution either by additional police cars on the streets or via changes to normal traffic flow.

directions, $\boldsymbol{WindDir_{it}}$[19]. Wind direction is known to influence concentrations of air pollutants and has been previously employed successfully as an instrument for air pollution (see for example Anderson, 2015). We allow for the influence of wind direction on pollution (ρ_i) to differ between five regions of London (Central, North, South, East, West)[20]. We do so because London covers a large area and wind patterns may transport pollution from different sources located in and around the city, which may result in the same wind direction having differential effects in different parts of the city. By allowing the first stage effect of wind direction on air pollution to differ between regions our approach is similar to that of Deryugina et al. (2016) who study the short-term effect of fine particulate matter exposure on mortality and medical costs among the elderly in the United States. We again include the same set of control variables and fixed effects used in our first empirical strategy described above. Our key identifying assumption is that – after controlling for weather conditions, fixed effects and other control variables – the average wind direction in ward *i* on day *t* is unrelated to criminal activity in ward *i* on day *t*, except through its influence on air pollution.

V. Results

a. Main Results

Table 2 reports on the link between air pollution and crime using our baseline model. In the first two columns we present cross sectional correlations between crime and ambient

[19] More precisely, we use as instruments the share of hours in the 24 hours of each day in which the principal direction of wind has been identified to belong to the three quadrants 0-90°, 91-180°, 181-270° respectively. The fourth quadrant serves as the baseline wind direction.

[20] The choice of regions is somewhat arbitrary, but results are robust to different groupings. In the results reported in this manuscript, we group boroughs into five regions as follows: West (Brent, Ealing, Harrow, Hillingdon, Hounslow, Richmond Upon Thames); North (Barnet, Enfield, Haringey, Waltham Forest); East (Barking and Dagenham, Bexley, Havering, Newham, Redbridge); Central (Camden, Hackney, Hammersmith and Fulham, Islington, Kensington and Chelsea, Tower Hamlets, Westminster); South (Lambeth, Southwark, Wandsworth, Bromley, Croyden, Greenwich, Kingston Upon Thames, Lewisham, Merton, Sutton).

pollution. The coefficient estimate in column 1 suggests that an additional 10 AQI units increase crime by 6.4%. In column 2, we add our set of time varying controls for weather, police deployment and local economic conditions (e.g. unemployment rate). We find that additional 10 units of AQI are associated with an increase of 2.9% in crime. Whilst both of these estimates are statistically significant at the 1% level, they are cross sectional in nature which prevents causal interpretation.

In columns 3–6, we exploit the panel structure of the data to estimate models with time, Day of the Week and ward fixed effects. Column 3, which estimates a within ward regression, suggests that 10 additional units of AQI leads to a 2% increase in crime. The estimate for our preferred specification, which includes the full set of controls and fixed effects, is reported in column 5. We find that additional 10 units of AQI increase crime by 0.9%, an estimate significant at the 1 percent level. This estimate is economically significant and suggests that the crime rate in London is 8.4% higher on the most polluted day (AQI=103.6) compared to days with the lowest level of pollution (AQI=9.3). The coefficient also corresponds to an elasticity of 0.03 which is similar to the effect of air pollution on productivity of call centre workers in China (Neidell, 2017). Figure 3 complements our analysis in table 2 with a visual representation of the relationship between residual pollution and crimes. The figure clearly demonstrates that using variation within ward yield a strong positive link between pollution and crime. Finally, in column 6 of table 2 we use crime rate per 100,000 people as our dependent variable instead of our log specification. We find that 10 additional units of AQI leads to 0.46 additional crimes per a 100,000 people.

In table 3 we examine the possible non-linear relationship between pollution and crime by substituting our continuous AQI measure with dummy variables for different levels of pollution. The results reveal a monotonic positive relationship between pollution and crime. For example, column 4 which report estimates from our preferred specification suggests that criminal activity in London increases by 2.8% on days with AQI above 35. This estimate is statistically significant at at the 1 percent level and equivalent to 0.07 of a standard deviation, which is very large and similar to the estimated effect of a 9% increase in police activity (Draca et al., 2011). Importantly, we find that these large effects are present at levels which are well below current regulatory standards as an AQI score between 0-50 is classified by the U.S EPA as "Good". Therefore, our results suggest that tightening existing pollution regulation may be economically beneficial.

Whilst we believe that our above empirical strategy yields credible evidence on the causal link between air pollution and crime, we cannot conclusively rule out the presence of unobserved time varying correlated factors[21]. Therefore, in table 4 we reports estimates from our 2SLS strategy, where we use wind direction as an instrument for pollution. In the first two columns we replicate our preferred fixed effect strategy from table 3 with the original and IV samples (respectively) to verify that our results do not change due to the small reduction in the sample size. As evident from the table, the results are identical. In columns 3-6 we report our 2SLS estimates using different sets of fixed effects and control variables. The first stage results clearly show that wind direction is indeed a strong predictor of local air pollution concentration and can therefore be used as an instrument[22]. Our second stage estimates are also highly economically and statistically significant across all specifications. In our preferred specification, which is reported in column 6, we find that 10 additional instrumented units of AQI increase crime by 1.7%. This result correspond to an elasticity of 0.05 which is not statistically different from our fixed effect estimate.

[21] There are other potential empirical concerns in this context such as measurement error and reverse casuality which our IV approach should overcome.
[22] For a more detailed discussion on why wind direction is a good instrument for air pollution see our empirical strategy section.

b. Robustness Checks

We conduct several placebo exercises and robustness tests to further support the causal interpretation of our analysis. First, we perform a placebo exercise in which we test the link between crime and air pollution concentration on irrelevant days[23]. Table 5 present our first set of results, where we look at pollution levels in the previous week, month and year[24]. Column 4 replicates results from the preferred specification (table 2, column 5), which produce statistically significant estimates only for same day pollution. The results confirm that the link between pollution and crime is present only at the same day with no significant relationships between the placebo pollution readings and crime. In figure 4 we perform a complementary analysis, where we examine the relationship between crime and pollution, not only at the same day, but also on the five days before and after. The figure clearly shows that the main effect of pollution is indeed concentrated on the same day.

Given the count nature of our data, we also examine whether our results are sensitive to alternative models. More specifically, the concern is that the distribution of our crime data is positively skewed with many potentially meaningful 0 value observations (see figure 1). In appendix table A1, we report results from Poisson, Negative Binomial and log transformation models which include the full set of fixed effects and controls variables. In column 1, we add a constant (=1) to our log transformation and in columns 2-3, we use Poisson and Negative Binomial models respectively. As evident from the table, these specifications yield very similar estimates and we therefore conclude that our results are not sensitive to alternative models in the full sample.

[23] Similar approach to Ebenstein et al. (2016).
[24] More specifically, we replace our independent variable with 7, 31 and 365 days lagged pollution level.

c. Heterogonous Effect of Air Pollution

In this section we examine the heterogonous effect of air pollution across the income distribution and on different types of crime. The motivation for the former is to explore the popular notion that environmental externalities disproportionally affect certain groups of individuals across the income distribution (Hsiang et al., 2017). The motivation for the latter is twofold. First, to study whether some crimes are more sensitive to air pollution. Second, to use the results, in conjunction with our formal economic framework, to identify the underlying mechanism for our headline findings. In Figure 5, we examine the effect of different types of crime using our preferred fixed effect specification[25]. The results suggest that 4 out of the 5 major crime types are positively affected by pollution. In figure 6 we break up those 4 major crimes into sub-categories and find a significantly larger effect on crimes with relatively small magnitude of punishments. In the United Kingdom, indictable offences represent the more serious offences which usually go for trial in front of the Crown Court and may result in lengthy prison terms. We do not observe an effect of air pollution on offences which contain the largest portion of indictable offences, including murder, assault causing severe bodily harm and robbery. Meanwhile we do find positive and significant effects of air pollution on the number of offences for which punishment is less severe – including a large share of summary offences such as pickpocketing which are usually tried in Magistrates' Court and result in lighter sentences (if tried at all and not punished by warning or fine).

Next, we investigate whether our estimates vary across resident income groups. This analysis is challenging as we need to distinguish between two possible cases. First, different resident groups in the population may be exposed to different levels of pollution. Therefore, if the relationship between crime and pollution is nonlinear, those groups with higher exposure

[25] As some of the smaller categories contains many meaningful zeros, we decided to be conservative and use a Poisson model in this analysis in order to maintain comparable samples across crime types.

will be more affected by an additional unit of pollution. Second, the marginal unit of pollution may affect some groups more than others for other reasons (e.g. vulnerability)[26].

To examine these aspects, we stratify our sample of 624 wards according to their average house price as a proxy for income (Figure 7). In figure 8, we plot the point estimates and corresponding 95% confidence interval for each decile. We also include the long term average AQI levels for each decile and find that long term pollution concentrations tends to be larger in wards with higher average house prices. Overall, we find a U-shape relationship where the larger effects seems to occur at the tails of the distribution. This suggests that both dynamics which we described above might be at play at our spatial scale of measurement: (1) the estimated effect of pollution on crime is larger in wealthier wards which are exposed to higher pollution levels and (2) despite relatively low exposure, the effect of pollution on crime is also large in the poorest wards.

VI. The Underlying Mechanism

Our results so far support our initial hypothesis that altered behaviour under heightened pollution exposure results in a larger number of crimes committed. In this section we will leverage our rational choice framework to uncover the underlying mechanism for our empirical findings. More specifically, in section 2 we outlined that within the rational choice framework of crime, the effect of pollution on crime may be mediated through the following three channels: (i) the payoff from crime W_j^c increases relative to the cost of future punishment S_j^c which is discounted at the rate β, (ii) the probability of being punished p_j is lowered, or (iii) the potential offender's preferences $U_j(.)$ become more risk accepting. We will now explore these channels in more detail.

[26] For a full discussion on this subject see Hsiang et al. (2017).

Risk perception and risk preferences:

Changes that lead to more risk taking should be expected to also lead to more criminal offences. In the expected utility framework presented above, more risk taking and hence more crime, can result from changes in either risk preferences or in risk perceptions. Existing evidence does not support changes in risk perception or risk preferences as an explanation for the observed effect of air pollution on crime. To explain an increase in crime, elevated levels of air pollution should be linked to a more optimistic evaluation of ones odds of getting away with a crime unpunished (lower p_j) or a change towards more risk loving preferences (higher $U''_j(.)$).

While the existing empirical evidence on air pollution and risk taking is limited, it suggests an association in the opposite direction. Heyes et al. (2016) provide suggestive evidence that risk taking in financial markets is lower on days with elevated levels of air pollution. However, one may doubt the relevance of the behaviour of investment professionals for the understanding of criminal activity. We thus perform an additional test, the results of which support a negative association between risk taking and air pollution. More specifically, we use weekly data on national lottery sales in England and Wales from (draws on Wednesday and Saturday of each week) for a rudimentary assessment of the link between risk taking and air pollution[27]. We find that a 10 point increase in the national average AQI on the day of a draw is associated with a 1.5% decrease in lottery sales accounting for weather conditions, day of the week, month and year of the draw.

Finally, a negative association between air pollution and risk taking is in line with the medical literature. Experimental evidence documents that, if anything, subjects become more risk averse when administered the stress hormone cortisol (Kandasamy et al., 2014) or when

[27] We use data on Main Sales (Saturday and Wednesday) in the UK National Lottery as collected by http://lottery.merseyworld.com. We run various specifications at times including weather controls (temperature, relative humidity, their interaction, wind speed and precipitation) as well as fixed effects for Saturday/Wednesday draws, the month and the year of the draw. Data cover all weeks in 2009-2014. The full set of results from our lottery analysis is available upon request.

exposed to physical stress (Porcelli and Delgado, 2009). As we discuss further below, acute exposure to air pollution has been linked to elevated levels of cortisol (Li et al., 2017). We would consequently expect to result in individuals becoming more risk averse when exposed to higher levels of pollution. In sum, both existing empirical evidence and our rudimentary analysis using lottery sales suggest that if anything air pollution may reduce risk taking behaviour and thus is unlikely to explain the observed increase in criminal activity on polluted days.

Perceived payoff vs. punishment: The potential role of discounting

If we wish to maintain the rational choice framework outlined above, and by the principle of exclusion, our results suggest that the increase in criminal activity may be driven by changes in the perceived gain relative to the punishment. Such a change in the perceived costs and benefits of a criminal offence can be driven by two changes – an increase in the perceived benefit (W_j^c), or a decrease in the perceived cost (S_j^c) discounted at the rate β,

A first channel through which pollution may affect crime is by increasing the perceived benefit (W_j^c). While it is plausible that heightened aggression (or similar effects on emotional disposition) might drive an increase in perceived benefit of interpersonal crime, it seems unlikely that altered emotional disposition affects the perceived benefit of crimes that are economically motivated and often committed by "professional" criminals. For example, we would not expect the emotional disposition of a pickpocket to significantly alter her expected gain from theft. We find that pollution drives most types of crimes (Figure 5), not only those which are interpersonal but also those which are more economically motivated[28]. Therefore,

[28] This is in line with a recent paper in the psychology literature, which finds an association between air pollution and a wide range of crimes in the United States (Lu et al., forthcoming).

we conclude that an increase in the perceived benefit (W_j^c) of crime is not consistent with our findings.

Whilst we do not expect air pollution today to influence sentencing (S_j^c) which occurs in the future, there is evidence from the medical literature which suggests that air pollution exposure may alter the relative perceived costs of punishment by raising the effective discount rate (β) applied to the future prospect of punishment. Acute exposure to elevated levels of air pollution has been linked to heightened concentration of stress hormones. In a rare experimental study, Li et al. (2017) provide evidence that acute exposure to elevated levels of PM2.5[29] leads to significant increases in cortisol (hydrocortisone), cortisone, epinephrine, and norepinephrine. Changes in blood levels of stress hormones are in turn expected to result in behavioural change. More specifically, heightened concentrations of stress hormones, especially cortisol, have been shown to alter time-preferences. In a controlled experiment, Riis-Vestergaard et al. (2018) find that subjects that were administered cortisol 15 minutes before the experimental task exhibited a strongly increased preference for small immediate rewards relative to larger but delayed rewards. The same was found in studies that randomly assigned physical stress rather than administering stress hormones. Again, individuals subject to physical stress (or pain) exhibited greater impatience than relevant control groups (Delaney et al., 2014; Koppel et al., 2017). In sum, acute exposure to elevated levels of air pollution (PM2.5) may temporarily increase the discount rate applied to intertemporal trade-offs via its effect on blood levels of stress hormones. Increased discounting lowers the cost associated with potential future punishment (S_j^c) and consequently results in an increase in criminal offences. Increased discounting also has the potential to reconcile the increase in crime (where potential

[29] Li et al. (2017) conduct a randomised, double-blind crossover trial where subjects (college students) have air purifiers installed in their dormitories for a period of 9 days. Some purifiers are functioning (mean PM2.5 exposure of 24 mg/m3), others are not (mean PM2.5 exposure of 53 mg/m3).

future punishment is discounted relative to immediate gains) with the observed decrease in lottery sales (where potential future winnings are discounted relative to immediate ticket costs).

VII. Conclusion

This paper investigates the potential link between ambient air pollution and crime. Using two separate identification strategies, we find that daily variation in air pollution is positively linked to higher crime rates in London. We also find that pollution affects most crime types but appears to have larger effects on crimes which are less severe. Based on the rational choice model and our empirical results, we conclude that the underlying channel for our findings is likely to be higher discounting of future punishment on high pollution days. Finally, we investigate whether our estimates vary across resident income groups and find a U-shape relationship where the larger effects seem to occur at the tails of the distribution.

Our results provide evidence that environmental factors are an important determinant of crime. Whilst previous studies focused on weather conditions, which are unlikely to be shaped by policymakers, we have studied an environmental condition which can be regulated. Our results suggest that improving air quality in urban areas by tighter environmental policy may provide a cost effective way to reduce crime. Furthermore, our results are present at levels which are well below current US Environmental Protection Agency (EPA) and UK Department for Environment, Food & Rural Affairs (DEFRA) standards which further suggest that it may be economically beneficial to lower existing guidelines. Finally, given the link between air pollution and crime, our results therefore suggest that examining the effects of air pollution on health impacts alone, may lead to a substantial underestimation of its societal costs.

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Table 1

Descriptive Statistics

Variable	All (1)	By House Prices: Low (2)	By House Prices: High (3)
Crime (log)	1.39	1.43	1.36
	(0.67)	*(0.64)*	*(0.70)*
Crime (# per 100k population)	34.06	32.73	35.38
	(38.43)	*(24.93)*	*(48.25)*
Air Quality Index (AQI)	30.06	28.51	31.60
	(9.177)	*(8.060)*	*(9.934)*
PM10	28.05	26.70	29.40
	(10.35)	*(9.863)*	*(10.65)*
Nitrogen Dioxide	50.00	46.11	53.90
	(21.06)	*(18.15)*	*(22.96)*
Sulfur Dioxide	4.710	4.667	4.752
	(3.492)	*(3.600)*	*(3.380)*
Ozone	33.17	33.94	32.39
	(17.86)	*(17.81)*	*(17.86)*
Temperature	11.76	11.86	11.67
	(5.805)	*(5.763)*	*(5.844)*
Relative Humidity	76.63	75.51	77.75
	(11.42)	*(11.46)*	*(11.28)*
Wind Speed	7.588	7.435	7.741
	(4.036)	*(3.712)*	*(4.330)*
Rainfall	1.581	1.497	1.670
	(3.526)	*(3.261)*	*(3.786)*
Unemployment	0.0506	0.0497	0.0514
	(0.0155)	*(0.0152)*	*(0.0158)*
Tube activity (million # per week)	1.677	1.721	1.632
	(2.248)	*(2.304)*	*(2.190)*
Police deployment (log)	0.527	0.469	0.585
	(0.379)	*(0.293)*	*0.441*
Observations	455520	227760	227760

Notes: Standard deviations are in parentheses. Each observation corresponds to one of 730 days and one of 624 wards. Data as described in the text from the following sources: Air pollution data from DEFRA (2017), weather conditions from the Met Office (2012), house prices from HM Land Registry (2017), and crime data from Draca et al. (2011).

Table 2

Pooled OLS and Fixed Effect Models of Air Pollution's Impact on Crime

	Polled OLS		Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)
AQI (10 units)	0.064***	0.029***	0.020***	0.009***	0.009***	0.457***
	(0.0124)	(0.0101)	(0.0041)	(0.0025)	(0.0025)	(0.1134)
Controls	N	Y	Y	Y	Y	Y
Ward FE	N	N	Y	Y	Y	Y
DOW FE	N	N	N	Y	Y	Y
Year-Month FE	N	N	N	N	Y	Y
R-squared	0.007	0.060	0.372	0.383	0.385	0.688
Observations	419,210	398,437	398,437	398,437	398,437	433,277

Notes: Each column in the table represents a separate regression. In column (1)-(5), the dependent variable is the (log) number of criminal offences per day and ward and in column (6) the dependent variable is the crime rate per 100,000 people. AQI is based on air pollution readings from the three closest AURN monitoring stations (weighted by inverse squared distance). Control variables include weather characteristics (temperature, relative humidity and wind speed),ward-level police deployment and unemployment levels. Standard errors are cluster-robust in two dimensions, over wards and dates. * p<0.1, ** p<0.05, *** p<0.01.

Table 3

Air Pollution's Impact on Crime

	Polled OLS		Fixed Effects	
	No Controls	Controls	No Controls	Controls
	(1)	(2)	(3)	(4)
Dummy for AQI >20 & <= 25	0.068***	0.021**	0.039***	0.014**
	(0.0110)	(0.0089)	(0.0090)	(0.0054)
Dummy for AQI >25 & <= 30	0.096***	0.021	0.056***	0.017***
	(0.0159)	(0.0140)	(0.0115)	(0.0064)
Dummy for AQI >30 & <= 35	0.134***	0.031*	0.070***	0.020***
	(0.0203)	(0.0183)	(0.0129)	(0.0071)
Dummy for AQI >35	0.177***	0.035	0.083***	0.028***
	(0.0279)	(0.0241)	(0.0142)	(0.0077)
Observations	419,210	398,437	419,210	398,437

Notes: See Table 2. Each column in the table represents a separate regression.

Table 4

Instrumental Variable Models of Air Pollution's Impact on Crime

	OLS		2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)
AQI (instrumnetd)	0.009***	0.009***	0.127***	0.018**	0.039***	0.017**
	(0.0025)	(0.0025)	(0.0361)	(0.0083)	(0.0141)	(0.0084)
Controls	Y	Y	Y	Y	Y	Y
Ward FE	Y	Y	N	Y	Y	Y
DOW FE	Y	Y	N	Y	N	Y
Year-Month FE	Y	Y	N	N	Y	Y
First stage (F-test)			22.91	13.69	13.25	13.54
Observations	398,437	396,521	396,521	396,521	396,521	396,521

Notes: See Table 2. Columns (3)-(6) instrumental variable estimates.

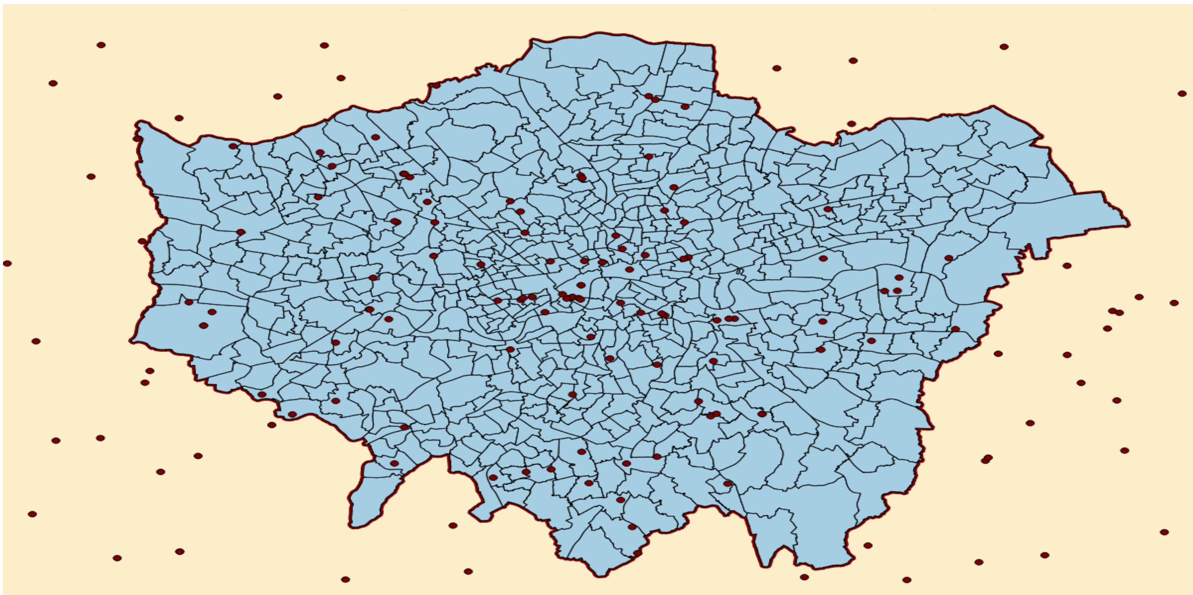
Table 5

Measuring the Relationship between Crime and Air Pollution on the Actual Day and Irrelevant Days

	Pooled OLS		Fixed Effects	
	No Controls	Controls	No Controls	Controls
	(1)	(2)	(3)	(4)
Day of Crime	0.062***	0.027***	0.022***	0.009***
	(0.0120)	(0.0095)	(0.0043)	(0.0024)
Previous Week	0.050***	0.017**	0.006	-0.001
	(0.0122)	(0.0085)	(0.0043)	(0.0023)
Previous Month	0.038***	-0.001	-0.010**	-0.002
	(0.0119)	(0.0085)	(0.0041)	(0.0023)
Previous Year	0.041***	0.003	-0.002	-0.001
	(0.0127)	(0.0094)	(0.0055)	(0.0032)

Notes: See Table 2. Each column in the table represents a separate regression.

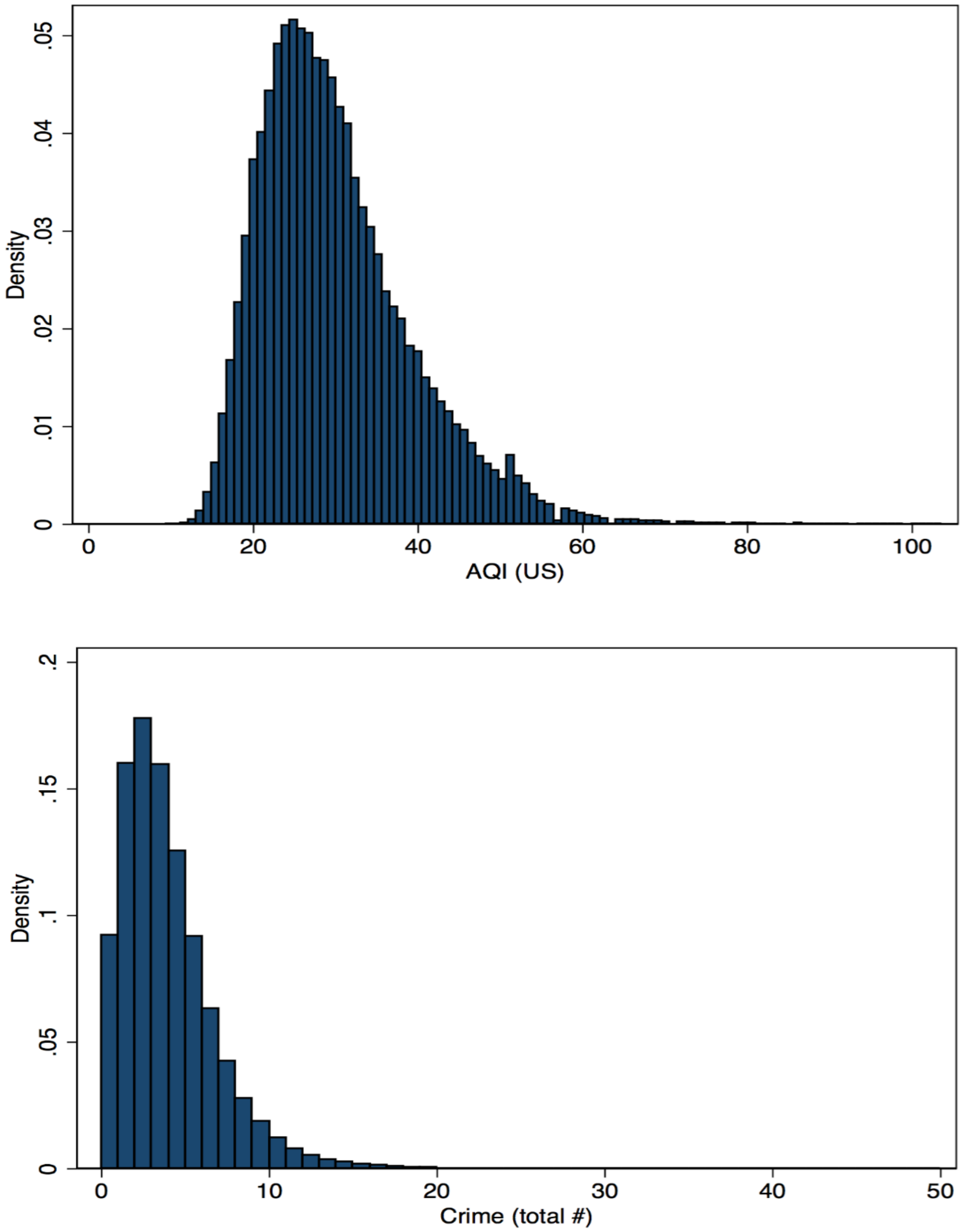
Figure 1
Geographic coverage - London wards, AURN/MIDAS stations



Notes: Geographic coverage of greater London, divided into 624 wards (excluding the City of London) and 96 AURN/MIDAS monitoring stations.

Figure 2

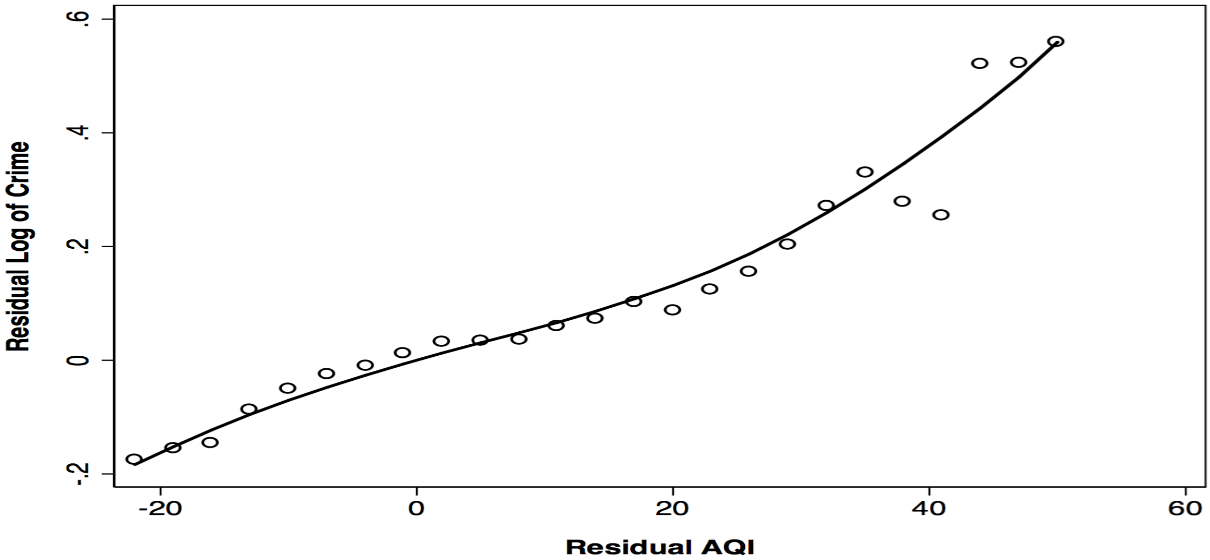
AQI and Crime - Density plots



Notes: Density plots of air quality index (AQI) measurements and total number of criminal offences by day and ward. Data as described in the text.

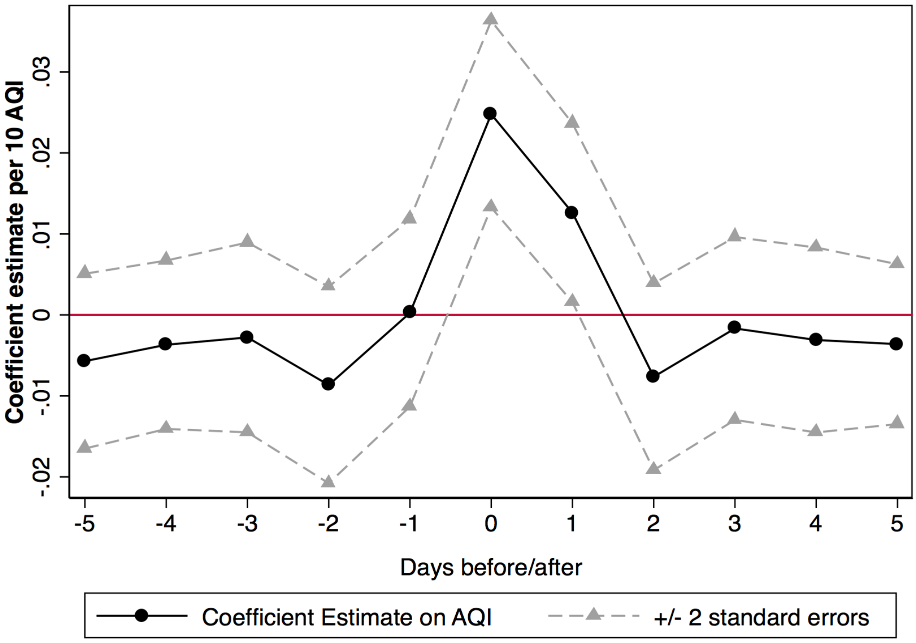
Figure 3

Residual AQI and Crime - Binned scatterplot



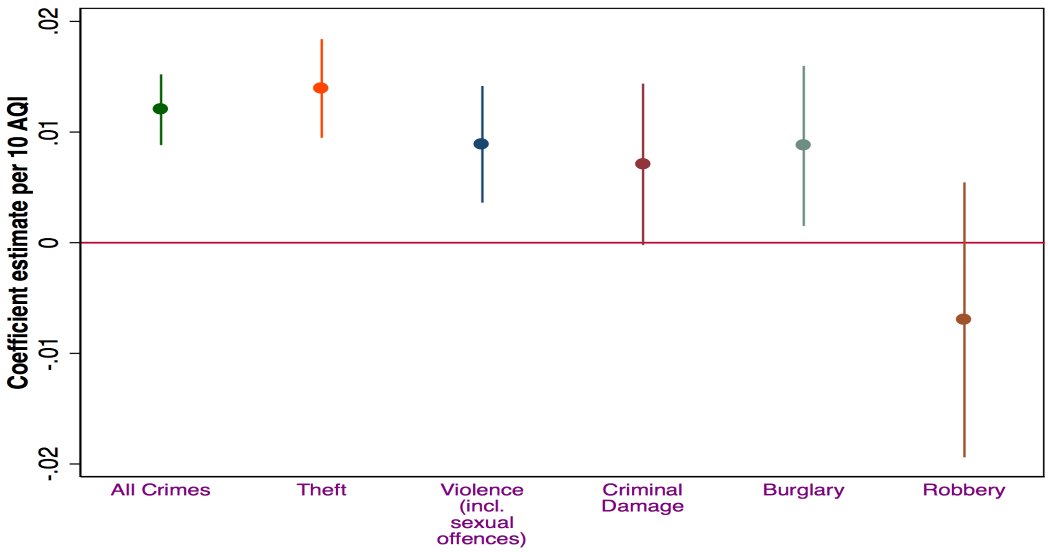
Notes: Plot of residual air quality index (AQI) and residual (log of) crime count. Residuals from a regression on ward fixed effects. Data as described in the text.

Figure 4
The Effect of Air Pollution on Crime - Lead/lag effects



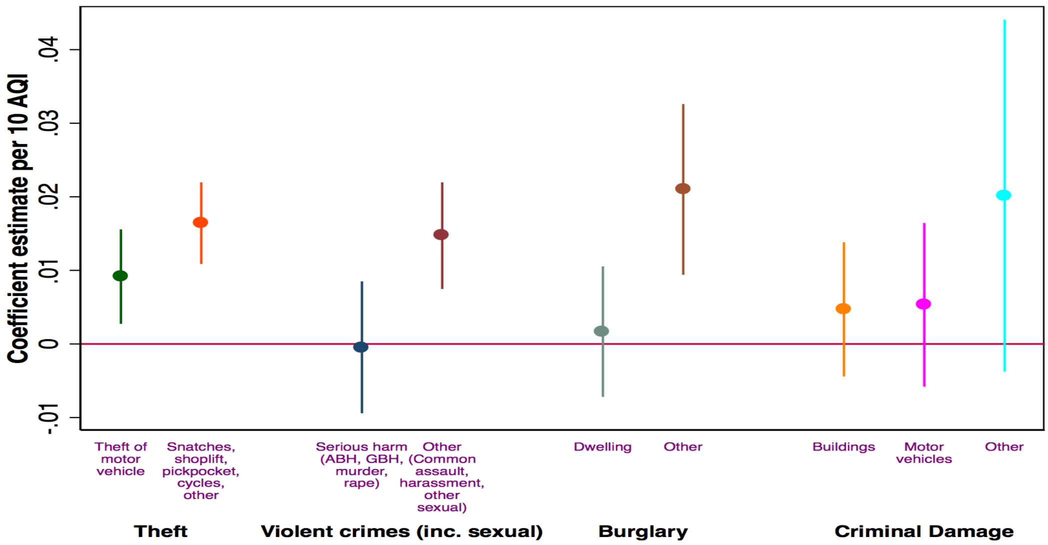
Notes: Coefficient estimates when including lead / lag AQI. Data as described in the text.

Figure 5
The Effect of Air Pollution by Major Crime Type



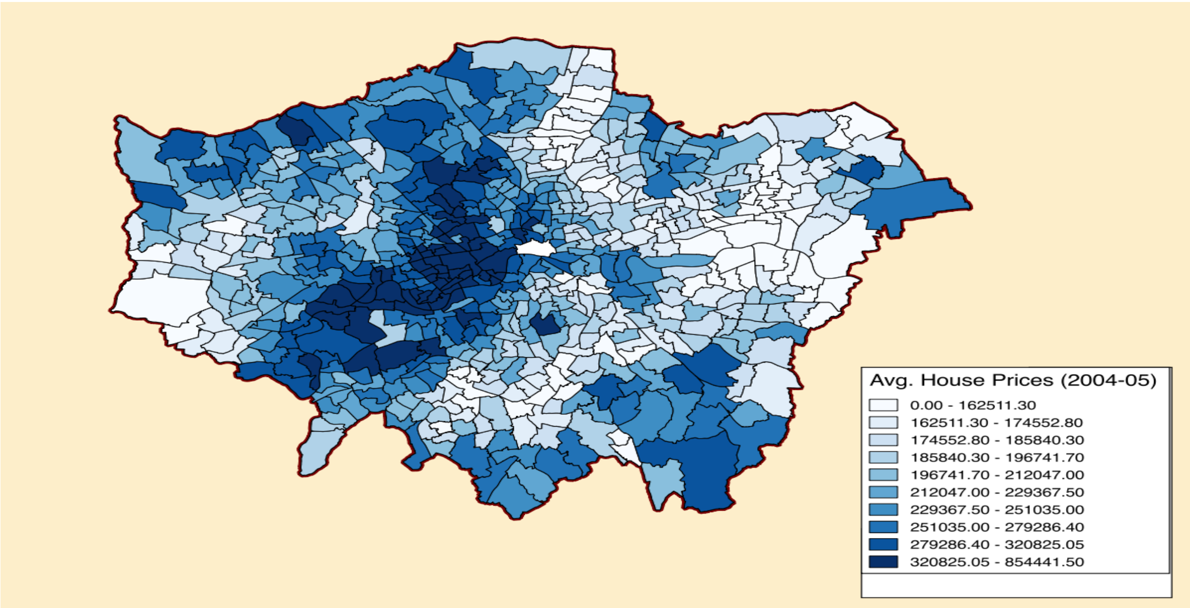
Notes: Coefficient estimates for separate estimations with different crime counts (5 largest major crime types) as outcome variable. Data as described in the text.

Figure 6
The Effect of Air Pollution by Crime Sub-Type



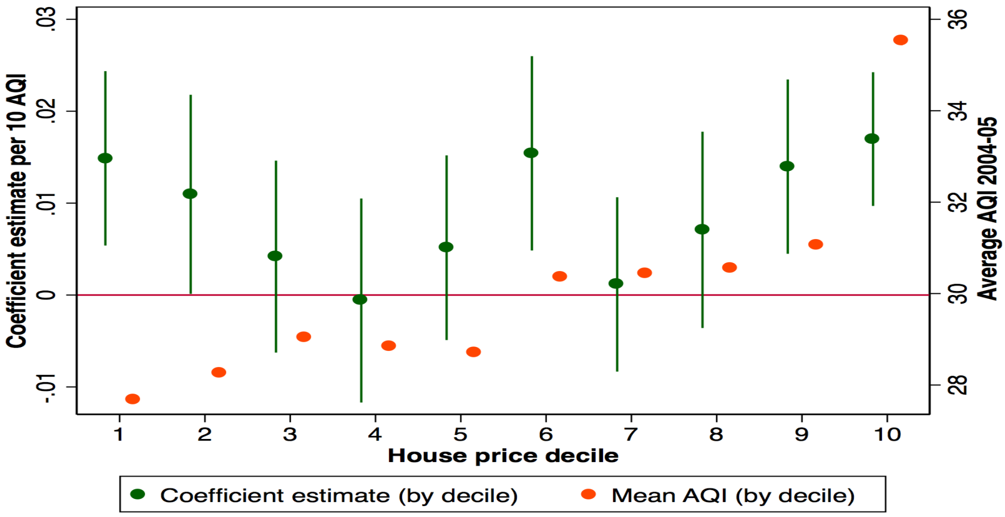
Notes: Coefficient estimates for separate estimations with different crime counts (crime sub-types) as outcome variable. Data as described in the text.

Figure 7
House prices - London wards



Notes: Average house prices over the 2004-2005 period by ward.

Figure 8
The Effect of Air Pollution on Crime by House Price Deciles



Notes: Coefficient estimates and 95% confidence intervals (left axis), sample stratified by 2004-2005 house price decile. Average AQI index by house price decile (right axis) Data as described in tl

APPENDIX: Table A1

Alternative Models of Air Pollution's Impact on Crime

	log+1 (1)	Poisson (2)	Neg. Bin. (3)
AQI	0.009***	0.012***	0.011***
	(0.0024)	(0.0016)	(0.0013)
Controls	Y	Y	Y
Ward FE	Y	Y	Y
DOW FE	Y	Y	Y
Year-Month FE	Y	Y	Y
R-squared	0.415		
Observations	433,277	433,277	433,277

Notes : Same specification as in column 5 of table 2. Outcome variable replaced with log(#crimes + 1) in column (1); equivalent Poisson model in column (2) and equivalent negative binomial regression model in column (3).