Too Polluted to Sin?

*Dirty Skies, Crime, and Adaptation Responses in Mexico City**

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Abstract

This paper estimates the non-monotonic effects of air pollution on criminal activity in a developing country setting and provides empirical evidence on the potential behavioral responses mediating this relationship. To do so, I combine daily administrative data on crime, air pollution, and sentiment polarity from millions of social media posts in Mexico City between January 2017 and March 2020. The identification strategy relies on highly dimensional fixed-effect models, non-parametric estimations of dose-response functions, and an instrumental variable approach that employs wind speed and wind direction as instruments for air pollution. My results suggest a causal and inverted U-shape relationship between air pollution and crime. Specifically, there is an inflection point after which marginal increases in air pollution negatively affect criminal activity. Exploring the mechanisms behind this relationship, I find that air pollution has the power to shape people's emotional states and mobility patterns. These results provide important insights for developing countries where pollution levels are dangerously high, and crime is still one of the most pressing issues. In particular, under certain circumstances, environmental regulation tailored to reduce air pollution must consider the presence of behavioral responses and these non-linear interactions with criminal activity in their design.

Keywords: Crime, Air pollution, Adaptation, Non-monotonic effects.

JEL Classification Codes: K42, Q53, D91

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1 Introduction

Air quality disparities among industrialized and developing countries have widened during the last decades. Rapid urbanization in low- to middle-income countries, coupled with explosive population growth, has created dense urban centers with levels of air pollution often exceeding five to ten times the limits recommended by the World Health Organization (WHO, 2021). While poor air quality is a severe threat in all the world's regions, it disproportionality affects urban areas of the developing world where mitigation opportunities are scarce. Yet, most research has taken place in richer countries where pollution levels are not usually high, and data and scientific knowledge are readily available.

Reducing the evidence gaps in air pollution across levels of development is imperative. Recent studies suggest poor air quality poses a more severe risk than previously thought. Ambient pollution could induce not only health-related problems but also alter a broader set of socioeconomic outcomes, often less visible such as labor productivity (T. Chang et al., 2016; Lichter et al., 2017; T. Y. Chang et al., 2019) and cognitive dysfunctions (Sanders, 2012; Ebenstein et al., 2016), and more difficult to measure, such as changes in human behavior (Burke et al., 2021; Aguilar-Gomez et al., 2022).

In this paper, I estimate the effects of air pollution on criminal activity in a developing country setting and provide evidence suggesting that behavioral responses mediate this relationship. In particular, I test for the presence of nonlinearities between air pollution and crime in Mexico City, examine how it compares to previous results in developed countries, and study the behavioral responses to air pollution as a potential explanation of these phenomena.

Mexico City offers a highly relevant setting for this analysis for two reasons. First, unlike similar urban areas elsewhere in the developing world, the local government maintains high-quality monitoring stations and highly disaggregated administrative crime data. Second, the city exhibits a high variance in air pollution, encompassing pollution levels common for both developed and developing countries. This variation allows me to estimate the marginal effect of air pollution on crime and compare this effect with the effects observed in industrialized countries.

To estimate the effect of air pollution on crime, I collect and combine daily administrative data on geo-localized crime records, air quality, and weather controls between January 2017 and March 2020. My final database includes 2,207,933 observations of daily crimes across 1728 neighborhoods in Mexico City. To test for nonlinearities in this relationship, I estimate Ordinary Least Squares models (OLS) using neighborhood and calendar fixed effects as well as a full set of weather controls. To account for any additional time-varying confounders, I implement an Instrumental Variable approach (IV) using wind speed and wind direction as sources of exogenous variation in local air pollution.

The OLS results suggest that, at the neighborhood-day level, an additional 10 units in the Air Quality Index (AQI) increases crime by 1.11%. However, since the dose-response between criminal activity and air pollution follows an inverted U-shape, once the air quality index surpasses $\sim$ 120 units, an additional 10 unit increase in the AQI decreases crime by 0.05%. The IV estimates report qualitatively similar results and show that after the turning point of 120 units is reached, increasing 10 units in the AQI decreases crime by 0.04%.

I provide evidence that the inverted U-shape between crime and air pollution is explained by two interacting yet opposing forces: (1) changes in emotional state and (2) avoidance behaviors implemented to reduce air pollution exposure when high levels are reached.

I use two approaches to examine how changes in individuals' emotional states could explain the pollution-crime relationship. First, I analyze whether some crimes are more responsive to air pollution than others. In line with previous results in the literature (Burkhardt et al., 2019; Herrnstadt et al., 2021), I estimate that air pollution increases violent crimes (e.g., assault, robbery, homicide, etc.) but not non-violent crimes (e.g., theft, falsification, white collar crime). These results indicate that poor air quality induces crimes that are more likely impulsive and mostly interpersonal. Second, I test whether behavioral responses, such as aggression and lack of self-control, may play a role in the pollution-crime relationship by analyzing how air pollution affects *expressed* psychological distress and emotional states. To do so, I employ Sentiment Analysis to construct indicators of expressed sentiment —as a proxy of emotional state— in 4,127,254 geo-localized Twitter posts. Sentiment Analysis, or opinion mining, is a Natural Language Processing tool that is used to interpret and classify the emotional tone from a body of text into a vector of sentiment scores (positive, negative, or neutral). My results show a positive correlation between negative sentiment and air pollution, suggesting that expressed sentiment is more negative on days with poor air quality.

To evaluate the presence of adaptation responses, I show there is a relationship between air pollution and mobility patterns. I use the number of "tweets from home" and daily metro ridership as outcome variables. First, I construct a "tweeting from home" variable as a proxy for being indoors. I find a positive correlation between pollution concentrations and being at home. Second, from administrative data on metro ridership—as a proxy for being outdoors—I find a negative correlation between air pollution and the number of metro journeys. These results suggest that adaptation responses play a role, especially when high pollution levels are reached, and therefore may also explain the non-monotonic relation between air pollution and crime.

Since adaptation responses might be correlated with or determined by income, I explore further whether the responses to air pollution differ across socioeconomic groups. Using a marginalization index, I show that it is precisely in wealthier neighborhoods where there is an inflection point, after which increases in air pollution lead to a decrease in violent crime. This result supports the hypothesis that more affluent areas are the ones that can invest in defensive behaviors, such as staying indoors or avoid specific areas, when levels of air pollution are too high.

Taken together, these findings provide a systematic empirical examination of air pollution, crime, and adaptation responses in a developing country setting. In doing so, this paper relates and contributes to the literature on the effects of air pollution on non-health-related outcomes and the behavioral responses that mediate those effects.

This paper speaks to the emerging literature on the effects of air pollution on crime, mainly focused on industrialized countries. Burkhardt et al. (2019) find that a 10% increase in PM2.5 is associated with a 0.14% rise in violent crimes using data from the continental US. Bondy et al. (2020) estimate that an additional 10 units in the Air Quality Index (AQI) increase crime by 1.2% in London, UK. Herrnstadt et al. (2021) find that in the City of Chicago, in neighborhoods located downwind of a major interstate, violent crime increases by

1.9%. Finally, Chen & Li (2020) use variations in the NOx Budget Trading Program in the US to show that reductions in air pollution lead to a decrease of 3.7% in violent crimes and 2.9% in property crimes. My paper contributes to this literature by providing evidence of this relationship in a developing country setting (Ayesh, 2021; Batkeyev & DeRemer, 2022), where it is common to find high levels of air pollution year-round. In particular, this paper takes advantage of the high variance in air pollution in Mexico City to estimate the marginal effects of air pollution at typical ranges for developing countries and then compare this to the marginal effects at ranges common for developed countries. Furthermore, this paper explores the presence of non-linearities in the relationship between air pollution and crime, having important implications for designing environmental and crime prevention policies.

In studying the mechanisms underlying the effects of air pollution on crime, this paper also adds to the literature on behavioral responses to air pollution. Mounting experimental evidence suggests that exposure to air pollution, even in small doses, could alter human behavior by affecting brain health. Research has shown that air pollution components could reach the brain, causing severe inflammation (Calderón-Garcidueñas et al., 2016; de Prado Bert et al., 2018; Martikainen et al., 2021) and damaging the central nervous system (Block & Calderón-Garcidueñas, 2009; Thomson, 2019; Calderón-Garcidueñas et al., 2021). Pollution-induced damage to the brain is associated with altered emotional states such as aggressiveness, anxiety, depression (Dantzer et al., 2008; Lu et al., 2018), dementia, and suicide (Calderón-Garcidueñas et al., 2018; Gładka et al., 2018; Niedzwiecki et al., 2020; Liu et al., 2021). Poor air quality is also associated with changes in stress hormones (Li et al., 2017; Thomson, 2019), which may exacerbate psychological distress and affect individuals' intertemporal preferences (Koppel et al., 2017). In the field of economics, recent empirical evidence also points out that environmental stressors have the power to shape human outcomes affecting expressed psychological distress, defensive purchases, and mobility (Baylis, 2020; Ito & Zhang, 2020; Burke et al., 2021; Aguilar-Gomez et al., 2022). In that regard, my paper contributes to the literature on behavioral responses by showing how the pollution-induced deterioration of emotional states might also affect interpersonal interactions such as violent crime.

This paper also contributes to the literature examining how air pollution alters the emotional well-being of urban populations using social media. In addition to expanding the study of how environmental stressors affects expressed sentiment to include a Spanish-speaking population—whereas previous research has only examined English and Chinese—my paper also uses state-of-the-art deep neural network-based methods to classify expressed sentiments online instead of the widely popular lexicon-based methods. These modern language models can exploit prior knowledge and automatically learn the meaning and order of words, which provides higher performance and accuracy in classification methods (Catelli et al., 2022), such as the ability to analyze sentiment in the Spanish language.

The remainder of this paper is organized as follows. Sections 2 and 3 present the institutional background and the conceptual framework that guides the paper. Section 4 describes the construction of data as well as the procedures used for data cleaning. Section 6 presents the empirical strategy and identification assumptions. Section 7 presents the main results and discusses the mechanisms. And finally, Section 9 concludes.

2 Institutional Background

Mexico City, the second largest city in the western hemisphere, offers a valuable laboratory for studying air pollution and crime. Its metropolitan area is home to about 20 million people, providing a large sample. It also has a reliable network of 34 air pollution monitoring stations across the city (see Appendix Figure A.1) that international organizations frequently audit. And, unlike other cities used to examine the pollution-crime relationship, Mexico City has pollution levels more typical of many mega-cities in the developing world. Furthermore, it has highly disaggregated administrative data on geolocated crimes, which is uncommon for similar cities in the region.

Air Pollution Air pollution has been a significant issue for decades, and for several years, Mexico City has been ranked as one of Latin America's most polluted metropolis. Although there have been substantial improvements in air quality during the last 20 years, rapid industrialization, unplanned urban development, and explosive population growth make spikes in airborne pollution common in the city. Geographic factors exacerbate severe air-quality problems. For example, the city's high altitude prevents carbon-based fuels from properly combusting; mountains and volcanos surround the inland basin on three sides which traps pollution in the valley; intense solar radiation, especially during the warm season, accelerates the formation of air pollutants.

Mexico City's government monitors six criteria pollutants, but four major ones dominate the skies: Fine Particulate Matter (PM_{25}), coarse Particulate Matter (PM_{10}), Ozone (O_3), and Nitrogen Dioxide (NO_2). During my analysis period, PM_{25} exceeded the World Health Organization's (WHO) recommended threshold 87% of the days, NO_2 97% of days, and Ozone and PM_{10} more than 50% of days.

Given the diverse set of pollutants and their high concentrations, the city disseminates pollution information through the Air Quality Index (AQI), a composite measure of six criteria airborne pollutants. According to this index, a value lower than 50 is considered safe for human health, while values above 100 are regarded as risky. In Mexico City, the AQI usually reaches dangerously high levels (see Figure A.3), with a mean value of 90.5. In contrast, the AQI in other cities studied before, like London in the UK, rarely surpasses 40.

Meteorology Mexico City has a subtropical highland climate with low humidity and warm temperatures during the day, cool nights during the summer, and cold nights during the winter. Over the year, the temperature varies between 6 °C and 25 °C, and it's rarely below 3 °C and above 30 °C. The warm, dry season goes from March to May, followed by a rainy season from June to September, and a cool, dry season from October to February. Mountains and volcanoes shield the city on three sides so winds are weak inside the valley; while the predominant wind direction varies throughout the year, the wind blows most often from the south.

Crime Mexico City was one of the first cities in Latin America to publish geolocated crime data. The crime records include reported and red-handed crimes, latitude, longitude, and sometimes the sex and age of the victims. Crime rates are high in Mexico City, although they are relatively low compared to other regions of the country. During 2017, 2018, and 2019 general crime rates were 2,342, 2,618, and 2,486 per 100,000 residents, respectively. According to the National Urban Security Survey of 2019, 62.1% of people reported feeling unsafe in their neighborhood. The most common crimes in the city are robbery, carjacking, kidnapping, and homicide.

3 Conceptual framework

Adaptation responses and the role of potential non-linearities If there are non-linearities in the crime-pollution relationship, looking only at cities with moderate concentrations may not help us to identify how pollution might affect crime—and related behavior—when pollution levels are very high. In particular, assuming a monotonic relationship between ambient pollution and crime, especially at high levels of air pollution, could bias the results if there is an inflection point after which marginal increases in pollution are more or less damaging. Thus, making it more likely to either overestimate or underestimate the effects of air pollution on crime.

In that regard, Arceo et al. (2016) argue that external validity of the estimated effects of air pollution may be limited if data from areas with low pollution levels is used to extrapolate the impact of air pollution to high pollution environments. For example, consider the setting where the effects of air pollution become less damaging when concentrations reach a cripplingly high level rarely reached in a cleaner city. Using estimates from places like London, Chicago, and other US cities (Burkhardt et al., 2019; Bondy et al., 2020; Herrnstadt et al., 2021) would give an incomplete view of the pollution-crime relationship in the proposed setting. In particular, extrapolating the estimates from those cities to many of the developing world's megacities that regularly exceed WHO limits by wide margins may lead us to overestimate the effects of air pollution on crime.

Air pollution's effects on crime may also be highly dependent on people's behavior, how easy it is to know when pollution is dangerous, and how costly it is to engage in adaptation strategies to reduce exposure. For example, staying indoors or investing in facemasks or air purifiers. This is especially important when studying the potential effects of environmental regulation to reduce air pollution, where the interaction between pollution exposures and income may be heterogeneous. For example, people are generally more likely to engage in defensive investments when exposed to high pollution levels (Ito & Zhang, 2020), especially when exposure is common. Thus, the effects of reducing air pollution could be lower with active adaptations in place. However, if investments are costlier, as is usually the case in the developing world (Arceo et al., 2016), adaptation responses may be limited, at least for poorer individuals. Hence, the effects of reducing air pollution could be larger in this setting.

In the first part of the empirical strategy, and based on this framework, I provide evidence of the nonlinearities in the relationship between air pollution and crime in Mexico City. In particular, I show an inflection point after which marginal increases in air pollution reduce crime. Then, in the second part, I explore the mechanism and argue that air pollution has the power to shape human behavior. First, I use expressed sentiment in social media posts and show that air pollution correlates to negative sentiment. Second, I use mobility measures to argue that adaption responses are in place, especially when high levels of air pollution are reached. Finally, I show that adaptation responses are heterogeneous, and wealthier neighborhoods are those engaging in them.

4 Data

I combined multiple administrative data sources on crime records, air pollution, weather, environmental alerts, and metro journeys with scraped data on social media posts from January 2017 to March 2020.

Crime The Attorney General's Office in Mexico City (Fiscalia General de Justicia) maintains a crime database that contains incident-level reported and red-handed crimes by type, including date, time, latitude, and longitude at which crimes occurred. I collapse incidence-level data into the neighborhood-day level, assigning crimes to each of the 1728 neighborhoods in the city.[1]

Weather and Air Pollution Daily monitor-level weather data is obtained from the Atmospheric Monitoring System (SIMAT)'s data portal. This agency uses 28 ground-based monitoring stations to measure hourly average temperature, relative humidity, wind speed, and wind direction. SIMAT also measures concentrations of primary air pollutants, including

[1]Appendix Figure A.2 maps the administrative divisions and topography of Mexico City.

PM2.5, PM10, Ozone, CO, NO2, and SO2 from 34 monitoring stations[2] across the city, and maintains historical records of the environmental alerts that have been issued due to air pollution. I aggregate monitor readings to the daily level by averaging across hourly observations.

Rainfall data is obtained from satellite-based readings from NASA's GPM IMERG Level 3 data, which provides daily measures with a spatial resolution of $0.1° \times 0.1°$.

My main pollution measure comes from the city's Air Quality Index (AQI) computed following the Mexican environmental standard NADF-009-AIRE-2017.[3] This index is a composite pollution metric based on the six primary air pollutants that run from 0 to 500. The higher the value, the greater the level of air pollution and associated health concerns. An AQI value of 50 units indicates a low risk to human health, while for values above 100, air quality is unhealthy.

I assign daily pollution and weather readings to neighborhoods using the inverse distance weighted average of the five closest monitoring stations to each neighborhood's centroid.[4]

Social Media I scrape and gather unstructured text data from 4,127,254 geotagged Twitter updates[5] posted within Mexico City's boundaries from January 2017 to March 2020. This dataset includes the date, time, geographic coordinates, username, and text in the tweet.

To transform the sample of tweets into data for my analysis, I use Natural Language Processing (NLP) algorithms designed to extract and quantify sentiment from text data. I use *pysentimiento* (Pérez et al., 2021), a Python toolkit for sentiment analysis and text classification specializing in Spanish. This toolkit uses models that can learn context and meaning from text by emulating the order of words in a sentence and tracking relationships

[2]These ground-based stations use equipment that meets the U.S. Environmental Protection Agency (EPA) requirements of Reference and Equivalent Methods (FRMs). These methods are considered the "gold standard" for monitoring air pollution and were created to sample and analyze air pollutants' ambient concentrations and guarantee that those measurements are reproducible. A set of more detailed explanations could be found in the SIMA's web portal `http://www.aire.cdmx.gob.mx/default.php?opc=%27ZaBhnmI=&dc=%27Yg==`

[3]This standard closely follows the U.S. Environmental Protection Agency (EPA) standard for the Air Quality Index.

[4]I test for an alternative number of stations, and the qualitative results are robust to that. The results can be found in Section 7.2

[5]Geotagged tweets refer to posts from users that provided consent to turn on the geolocation tags.

in sequential data. In particular, *pysentimiento* uses as a base model BETO,[6] a language model trained with 3 billion words fed by all the data from Wikipedia, TED talks, United Nations, Subtitles, and News Stories, among other sources in Spanish.

I use additional functions in *pysentimiento* to pre-process the piece of text in each tweet by converting emojis into descriptive words, normalizing laughs, and removing URLs, hashtags, punctuation, user handles, and repeated words up to three occurrences (see Table A.6). Then, from a piece of text (tweet), *pysentimiento* produces a vector of sentiment scores with the probability that the sentiment expressed is negative, neutral, or positive. My outcome of interest from this vector of sentiment scores is the number of tweets expressing negative sentiment.

I assign tweets and sentiment to neighborhoods using tweets' GIS coordinates and then aggregate the data at the neighborhood-day level. Appendix Figures A.5 and A.7 show the spatial distribution of the total tweet volume and the empirical distribution of negative sentiment. These figures suggest significant geographical variation in tweet volume across neighborhoods and a wide range of negative sentiment in my data. Furthermore, Appendix Figure A.8 illustrates that the behavior of negative sentiment over time seems to be accurate compared to the political and economic atmosphere in the city.

I use two mobility measures to investigate whether air pollution could alter people's movement patterns. The first variable is a proxy for mobility using each tweet's GIS coordinates and posting time as input. For each user, I select those tweets posted after 7 pm and before 8 am and define the average of the coordinates (latitude and longitude) of this sub-sample of tweets as each user's "home" location. Then, I construct a "tweeting from home" variable to classify tweets 1km or less from the identified user's "home" location. This "tweeting from home" variable captures those tweets posted from each user's home and, thus, indoor behaviors. The second mobility measure is the daily metro ridership in Mexico City. This measure comes from administrative data shared by the city's mobility authority, Secretaria de Movilidad (SEMOVI), and includes the number of daily passengers

[6]The base model is BETO, a BERT-based language model pre-trained using only Spanish data. BERT stands for Bidirectional Encoder Representations from Transformers, and it's a machine-learning model for natural language processing tasks such as sentiment analysis, text prediction, text generation, and summarization.

per metro station. I assign each metro station to a neighborhood based on location and then sum over all metro stations inside each neighborhood to get the total number of riders at the neighborhood-day level. The daily ridership works as a proxy of outdoor behavior in each neighborhood.

Table A.1 presents summary statistics at the neighborhood-day level. The original sample includes 2,207,933 observations of daily crimes across 1728 neighborhoods in Mexico City.[7] There is significant variation in crime and the Air Quality Index across neighborhoods and over time. During a given day, crime numbers range from 0 to 150 while the average number of crimes per neighborhood is 0.35. The AQI spans from 1.7 to 208 units, with a mean of 90.5.

5 Stylized facts

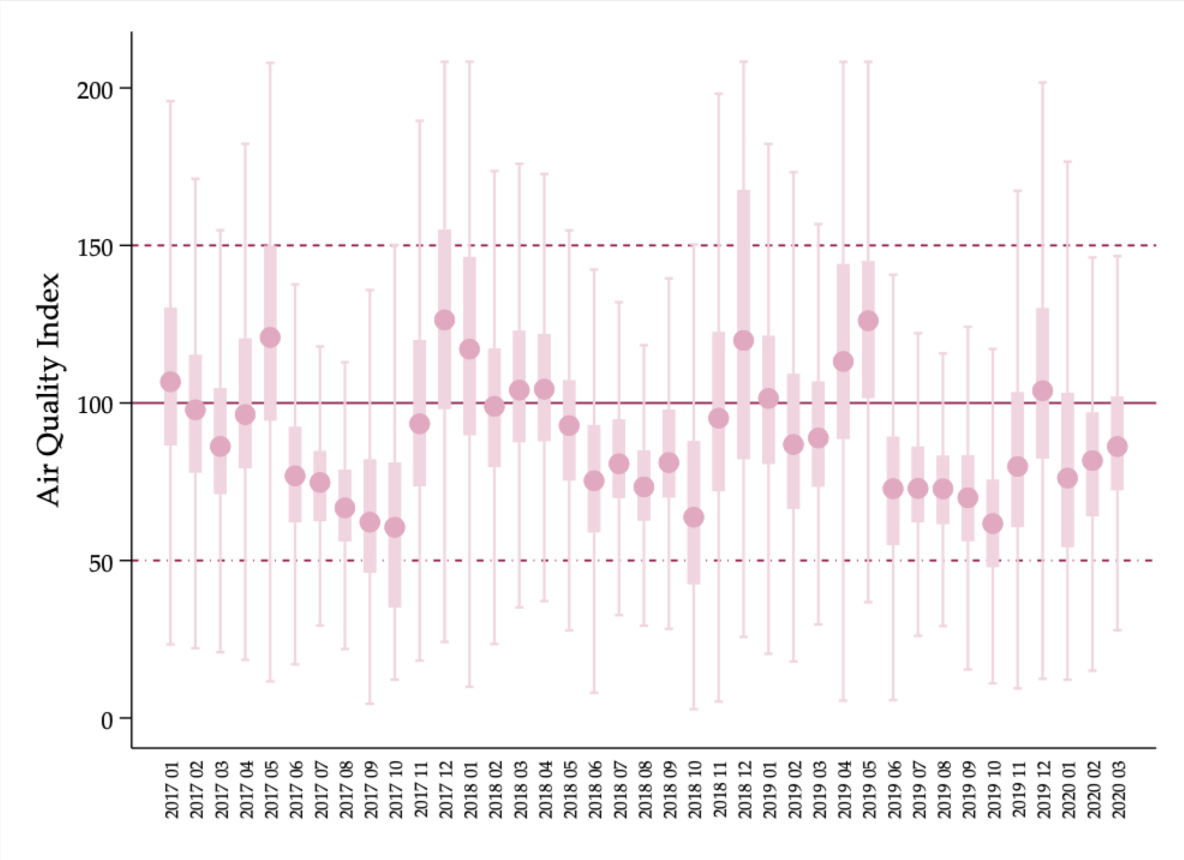
To motivate the main features of the empirical strategy in the following section, I start by documenting three stylized facts from the data. The first reveals that air pollution is seasonal and correlated with weather variables. The second illustrates the high spatial variation in criminal activities and its correlation with weather variables. Finally, the third shows that expressed sentiment and outdoor activity are correlated with air pollution, yet in opposite directions.

5.1 Air pollution is seasonal and often exceeds health-risk limits

Figure 1 shows a box plot for the air quality index's mean, interquartile range, and upper and lower adjacent values for every month in the sample period. It illustrates that the Air Quality Index (AQI) is consistently above what is considered safe for human health (dashed line at 50) as recommended by local authorities. In particular, the mean AQI was 90.56 during this period. Moreover, in 959 out of 1170 days in my sample, the readings from monitoring stations across the city reached values above 100 points (solid line), which is considered high risk for human health.

[7]Depending on the availability of controls and singletons in the panel data, observations might vary across specifications.

Figure 1: Air pollution is seasonal and often exceeds health-risk limits



Notes: This figure presents a box plot for the Air Quality Index (AQI) from January 2017 to March 2020. It reports the mean, interquartile range, upper and lower adjacent values computed from each month within the sample. The dashed line at 50 corresponds to the safe AQI limit for human health. The solid line at 100 represents the AQI limit considered high risk for human health. The dashed line at 150 corresponds to extremely high risk for human health.

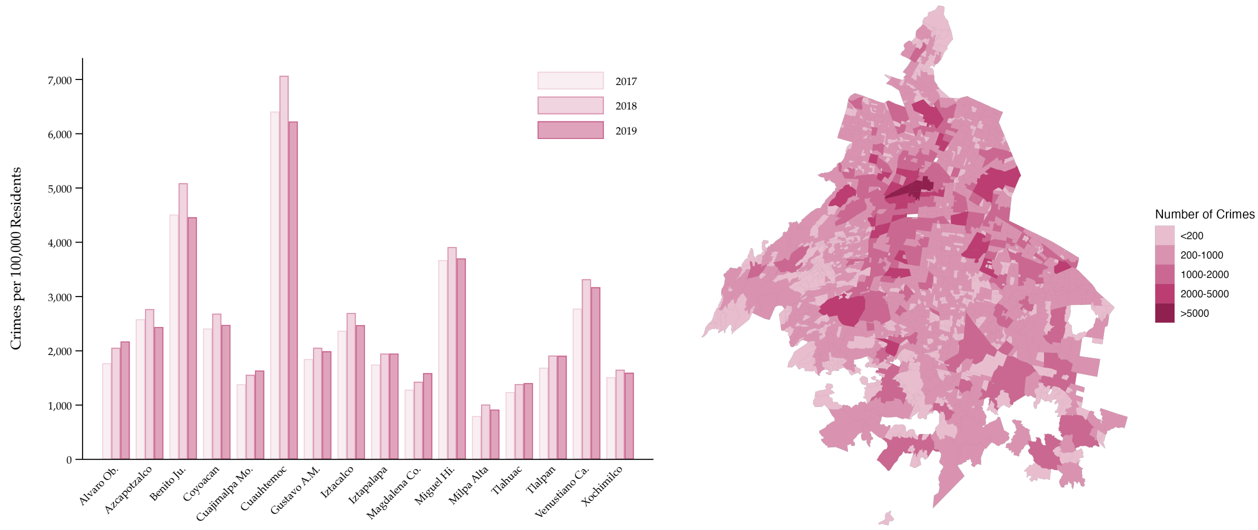
Despite the fact that air pollution is a year-round concern in Mexico City, Figure 1 illustrates that pollution is highly seasonal. The peak season coincides with the dry season between October and May, while the lower season coincides with the rainy season between June and September. Thus, it is essential to consider these seasonalities and weather conditions and control for them in the empirical strategy.

5.2 Crime is geographically dispersed and related to weather conditions

Panel A in Figure 2 shows that Cauchtemoc, Benito Juarez, Miguel Hidalgo, and Venustiano Carranza are the boroughs that routinely show the highest number of crimes per 100,000 residents during the period of analysis. Yet, Panel B shows that crime in Mexico City is still geographically dispersed. These results highlight the importance of accounting for location-specific and time-invarying characteristics that could drive crime at the neighborhood level.

Figure 2: Crime in Mexico city is geographically dispersed

Panel A: Crime Rate per Borough **Panel B:** # Crimes per Neighborhood



Notes: Panel A uses data from Attorney General's Office in Mexico City aggregated at the borough level. The panel shows the number of crimes per 100,000 residents by borough and year in Mexico City. It includes 16 boroughs and data from January 2017 to December 2019. Panel B uses the same data source but plots the total number of crimes per neighborhood during the analysis period. It includes 1729 neighborhoods from January 2017 to March 2020.

There are also time-varying characteristics that could affect crime. In particular, literature has shown that weather variables could also be related to criminal behavior (Cane et al., 2014; Burke et al., 2015; Cohena & Gonzalez, 2018). Appendix Figure A.4 shows this is also the case in my data. Using bi-variate regressions, I find that the number of crimes is positively correlated with temperature and rainfall and negatively correlated with humidity in this setting. Therefore, it is crucial to flexibly control for weather characteristics in the baseline specifications of my empirical strategy to rule out the possibility that weather is responsible for my results.

5.3 Social media sentiment and mobility are related to air pollution

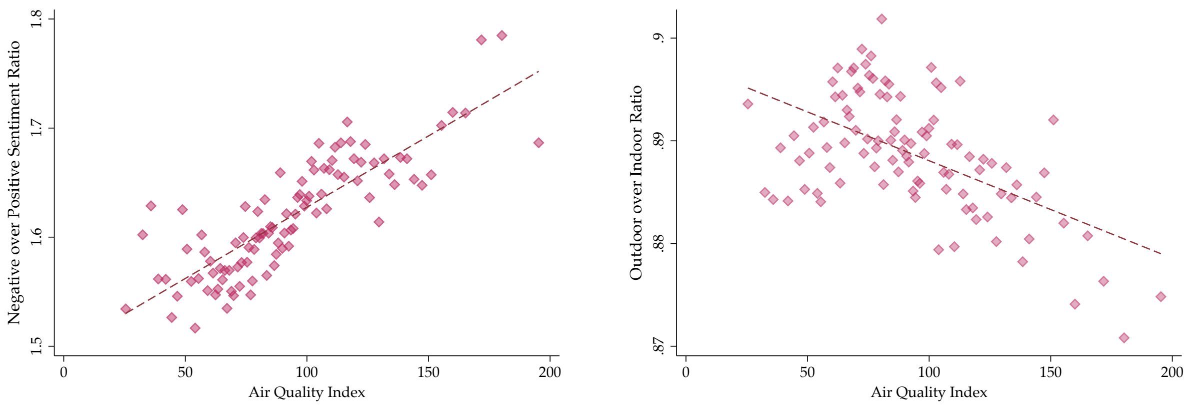
This paper uses social media data to measure expressed sentiment as a proxy of emotional state and to identify users' "home location" as a tool to describe mobility patterns. Figure 3 plots the relationship between posts from Twitter and the Air Quality Index—aggregated at the neighborhood-day level.

Figure 3 illustrates that two opposing forces exist when high pollution levels are reached. On one side, Panel A depicts the negative-over-positive sentiment ratio measured in my sample data in a binned scatter plot against air pollution. The negative-over-positive sentiment ratio is computed as the number of tweets expressing negative sentiment over positive ones. As illustrated in Panel A, there is a positive correlation between air pollution and the negative-over-positive sentiment ratio, suggesting that expressed sentiment is more negative on days with poor air quality.

On the other side, Panel B plots a binned scatter plot of the AQI and the outdoor-over-indoor ratio, defined as the share of tweets posted outside the identified users' "home location." The relationship illustrated in Panel B presents a negative correlation between air pollution and the outdoor-over-indoor ratio, thus, suggesting that poor air quality reduces outdoor activity.

Figure 3: Two opposite forces interact when high pollution levels are reached

Panel A: Negative Sentiment **Panel B:** Outdoor Activity



Notes: Data at the neighborhood-day level. Panel A plots a binned scatter plot of the Air Quality Index AQI and the negative over positive sentiment ratio from my social media sample. Negative (positive) sentiment refers to the number of tweets scored as expressing negative (positive) sentiment after applying NLP algorithms. Panel B plots a binned scatter plot of the AQI and outdoor over indoor ratio. Indoor (outdoor) refers to the number of tweets posted within (outside) each user's "home location".

6 Empirical strategy

6.1 Estimating the non-linear relationship between air pollution and crime

To estimate the non-linear effect of air pollution on criminal activity, it is essential to rule out potential confounding factors influencing this relationship. For example, economic activity and population density could determine both the intensity of crime and the presence of air pollution in a given area. Moreover, as motivated by the previous section, weather conditions and geographical characteristics could determine the spatial dispersion of particulate matter and the concentration of crime. I use two complementary identification strategies and a non-parametric specification to estimate this relationship and to overcome this empirical challenge. I explain all three in detail below.

Multidimensional Fixed Effects model I start by accounting for neighborhood-specific and time-invariant characteristics, as well as common shocks to all neighborhoods, by estimating the following econometric specification,

$$Crimes_{i,t} = \mu_i + \delta_t + \beta_1 \cdot Pollution_{i,t} + \beta_2 \cdot Pollution^2_{i,t} + \boldsymbol{X'}_{i,t}\boldsymbol{\Lambda} + \epsilon_{i,t} \tag{1}$$

where $Crimes_{i,t}$ is the total number of crimes in neighborhood i on day t and $Pollution_{i,t}$ represents a three-day mean value of the Air Quality Index (AQI) based on day t and the previous two days. This aggregation considers that accumulated exposure to air pollution may play a differential role in cities that generally experience pollution levels that exceed regulatory standards year-round, like Mexico City. The parameters of interest are β_1 and β_2, which respectively capture the linear and nonlinear components of the relationship of interest. I include the quadratic term to investigate if there is a peak point in the pollution-crime relationship.[8]

There is well-established evidence that weather conditions affect both pollution (Zannetti, 1990; Deryugina et al., 2019) and crime (Burke et al., 2015; Cohena & Gonzalez, 2018). I follow Deryugina et al. (2019) and control for a flexible function of temperature and weather variables. First, I generate indicators for daily maximum and minimum temperatures. The daily maximum includes seven bins, ranging from 5 degrees Celsius to 33 degrees Celsius, with each bin spanning 3 degrees Celsius, while the daily minimum includes six bins, ranging from -5 to 20 degrees Celsius. Second, I classify the daily relative humidity and precipitation in deciles and generate indicators for each of them. And third, I generate a vector $\boldsymbol{X}$ that

[8]Since the potential non-linearity may be mechanically imposed on the data by including the quadratic terms, I perform a non-parametric estimation of this relationship and study the effect of increasing one additional unit of air pollution on crime. Section 7 present the details and results of this estimation.

includes all the possible interactions between those weather variables. To ensure that β_1 is not capturing the effect of weather conditions over the previous two days, I also include two lags of the weather interactions.

Time and neighborhood fixed effects are represented by δ_t and μ_i, respectively. Including neighborhood fixed effects in the specification removes any potential time-invariant confounders and controls for geographic differences in crime and pollution. This will allow me to compare crime levels between days with high and low pollution levels within the same neighborhood. I also include day-of-the-week and month-by-year fixed effects to control any within-week and seasonal pollution and crime variation, respectively. ϵ_{it} is the idiosyncratic error term; I cluster standard errors at the neighborhood level to account for potential time dependency. Finally, given that crime is a count variable, I use a Poisson pseudo-maximum likelihood (PPM) estimation with multiple high-dimensional fixed effects Correia et al. (2020), that takes into account the censored nature of the dependent variable without requiring that the conditional variance must be equal to the conditional mean.[9]

Instrumental variable approach I recognize that air pollution is not randomly generated and will likely be measured with some error. Thus, the previous specification may not completely eliminate endogeneity concerns given by omitted factors that vary with time on the level of individual neighborhoods. For example, economic activity may cause changes in air pollution and also in criminal activity. In this case, β_1 and β_2 would be subject to bias in favor of the direct role of pollution in causing crime. Thus, I instrument air pollution with wind speed and wind direction to address these endogeneity concerns. More specifically, I estimate the following 2SLS specification:

$$Crimes_{i,t} = \mu_i + \delta_t + \beta_1^{IV} \cdot \widehat{Pollution}_{i,t} + \beta_2^{IV} \cdot \widehat{Pollution}^2_{i,t} + \boldsymbol{X'_{i,t}\Lambda} + e_{i,t} \tag{2}$$

$$Pollution_{i,t} = \eta_i + \phi_t + \boldsymbol{\Phi}\left(Wind^{Speed}_{i,t}; Wind^{Direction}_{i,t}\right) + \boldsymbol{X'_{i,t}\Gamma} + \epsilon_{i,t} \tag{3}$$

where $Crimes_{it}$ is again the total number of crimes in neighborhood i on day t, $\widehat{Pollution}_{it}$ is the corresponding prediction from the first stage (Equation 3), and $\boldsymbol{\Phi}$ is a parametric but

[9] I also estimate Equation 1 using OLS and a simple logarithmic transformation of the number of crimes plus one. I find qualitatively similar results which I report in the Appendix.

flexible function of wind that considers *both* the effect of wind speed and wind direction as well as *their interaction* on air pollution. To do so, I aggregate hourly monitor readings of wind speed and wind direction to the daily level averaging across hourly measurements. I include the same set of weather controls and fixed effects explained in detail in Section 6.1.

The model specification described in Equations 2 and 3 is motivated by previous results in the literature as well as by the data. Figure 4 illustrates how wind direction and speed strongly predict air pollution levels across neighborhoods over time. Panel A presents a correlation statistic plot for the average Air Quality Index binned by the dominant wind direction and wind speed over the entire period. As can also be corroborated in Panel B, wind speed is negatively correlated with the average air quality since high wind speeds help to dissipate air pollution. Similarly, this relationship varies in intensity depending on the quadrant of the dominant wind direction. Panel C shows that the average pollution levels directly depend on the predominant direction of wind across eight potential direction vectors.[10] For example, Panel C shows that air pollution is higher when the wind is blowing from the east, most likely because pollution concentrates in the mountainous formation in the southwest of the city.[11]

To capture the potential complementarity between wind direction and wind speed, I specify further that

$$(4) \qquad \mathbf{\Phi}\left(Wind_{i,t}^{Speed}, Wind_{i,t}^{Direction}\right) = \sum_{q \in Q} \delta_q \cdot \left(Wind_{i,t}^{Speed} \times \mathbb{1}\left\{Wind_{i,t}^{Direction} = q\right\}\right),$$

where Q represents the set of potential quadrants $Q = \{NW, NE, SW, SE\}$ and $\mathbb{1}(\cdot)$ is an indicator function.

The key identifying assumption when using wind as an instrument for air pollution is that, after controlling for weather variables and a rich array of fixed effects, the interaction between wind speed and wind direction only affects crime through its influence on air pollution.

One concern about using wind speed as part of the instrument is that wind speed

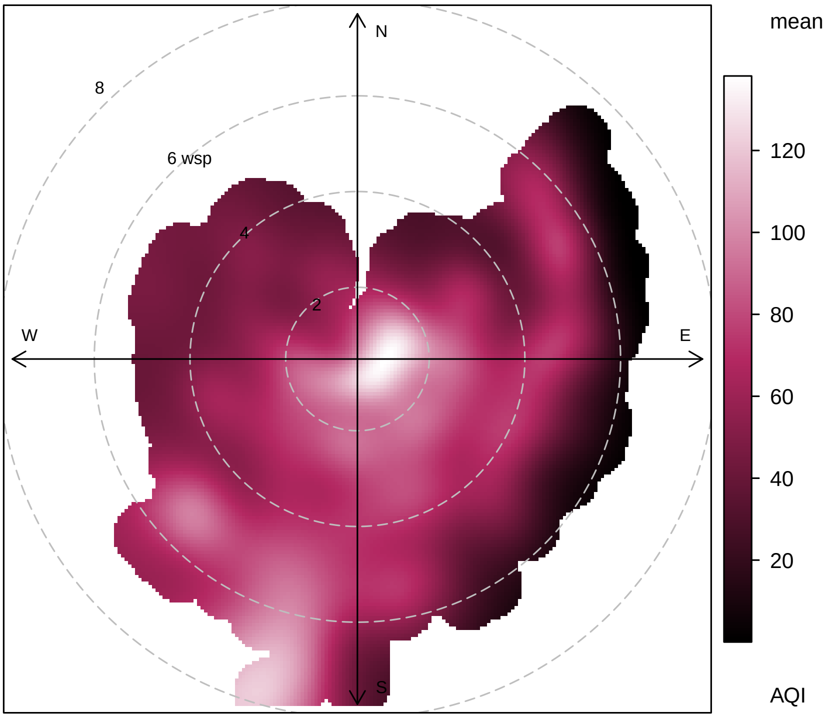
[10]The eight vectors are: north (N), south (S), west (W), east (E), northeast (NE), southeast (NW), southwest (SW), and northwest (NW)

[11]Figure A.2 shows the topographic terrain of Mexico City. Mountains surround the city in the southwest region, trapping the air when the wind blows from the North and the East.

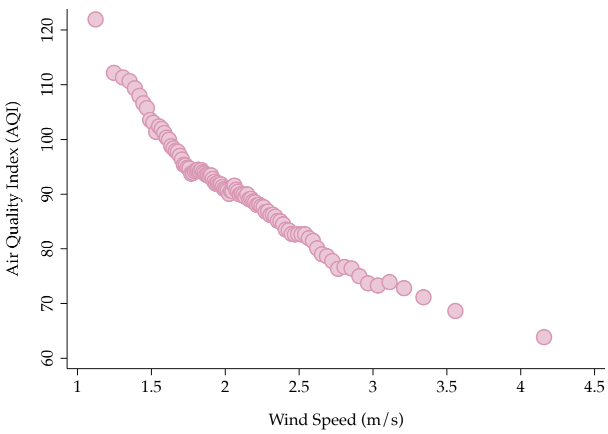
might directly affect the number of people on the streets and, consequently, the supply of victims of crime. Thus, the exclusion restriction would be violated if wind speed affected behavior. However, data suggest Mexico City usually experiences mild weather and wind speeds all year round, unlike marked seasons of high-speed winds typical in northern latitudes. In fact, the median wind speed during the whole period of the analysis is 2.1 m/s ($\sim$ 4

Figure 4: Wind speed, wind direction, and the concentration of air pollution

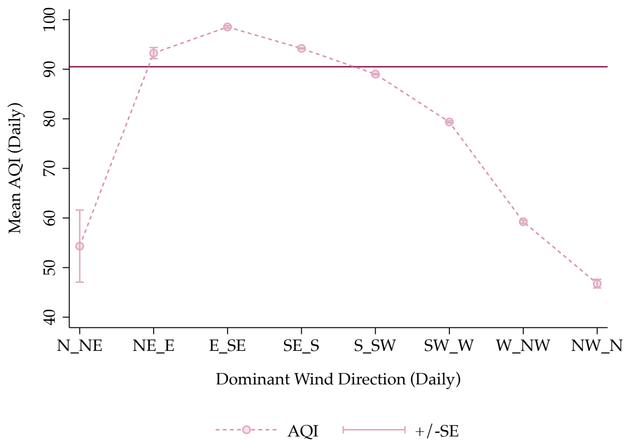
Panel A: AQI index across all wind speed and dominant wind direction combinations



Panel B: AQI vs. wind speed



Panel C: AQI vs. wind direction



Notes: Panel A plots the average AQI index across binned pairs of wind speed (concentric circles) and dominant wind direction (quadrants). Panel B presents a binned scatter plot of the air quality index AQI and average wind speed. Panel C plots the average daily AQI across all wind directions with 99% confidence intervals.

knots), which under the Beaufort Wind Scale[12] is considered as *light breeze* with no major impact on the land. Furthermore, Figure A.9 shows that there were very few days per year when the mean wind speed reached values above 3 m/s ($\sim$ 6 knots), which in any case is still considered as a *light breeze* under the Beaufort Scale.

Computing a dose-response function Another critical concern with the main specification is that the non-linearity may be mechanically imposed on the data by simply including the quadratic term and potentially resulting from over-fitting the data. To rule out this possibility, I perform a non-parametric estimation[13] of this relationship using a restricted cubic spline and by studying the effect of increasing one additional unit of air pollution on crime at different levels of air pollution.

7 Results

7.1 Inverted U-shape relationship between air pollution and crime

Table 1 presents the results of estimating Equation 1. Columns 1 and 2 show the estimated coefficients without including fixed effects. These results suggest that an additional ten units in the three-day average of the Air Quality Index (AQI) are associated with an increase in crime by 5.48% and 6.87%, respectively. However, this change doesn't occur linearly, as illustrated by the significant squared term. Column 2 flexibly controls for temperature and other weather variables, plus their respective lags, to ensure that the non-linearity is not driven by daily temperature (Burke et al., 2015). Columns 3-7 display the results after including various sets of fixed effects explained in detail in section 6.1. Column 4 shows that an additional ten units in the AQI's mean average leads to an increase of 1.04% in crime after including neighborhood fixed effects. My preferred specification includes a full set of fixed effects and is depicted in column 5. This column shows that an increase of ten units in the air quality index AQI leads to a 1.1% increase in the number of crimes.[14]

[12] The Beaufort Wind Scale classifies wind speeds and its effects at different levels. The scale starts with 0 and goes to a force of 12.

[13] Figure 6 shows the result of this estimation.

[14] Notice, however that the total effect of increasing 10 units in the AQI once we account for the non-linear effect (i.e., $\frac{\partial Crimes_{i,t}}{\partial AQI_{i,t}} = \frac{\beta_1}{10} + \frac{2}{100} \cdot \beta_2 \cdot AQI$) is actually 0.0206% when evaluate it at the mean.

I also add quarter-by-year and semester-by-year fixed effects in columns (6) and (7), respectively, to control for any seasonal variation at these levels. Since the significance and magnitude of my coefficients remain stable in columns (6) and (7), I conclude that my results are robust to such seasonality.

Table 1: Air pollution's impact on crime: PPML estimation

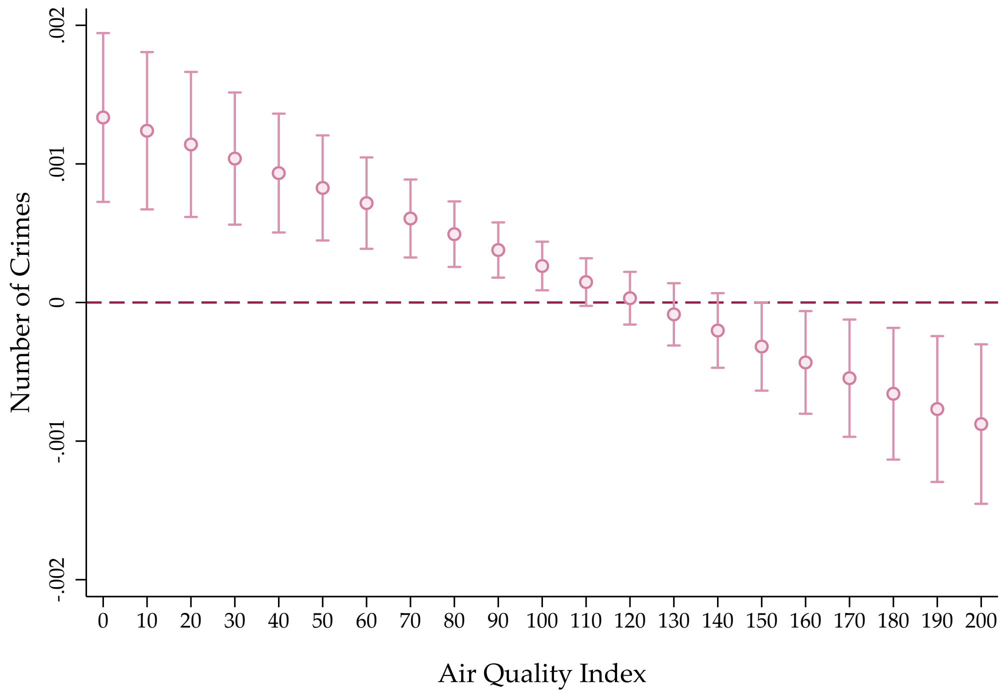
Dependent Variable:	Number of Crimes						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AQI (10 Units)	0.0548***	0.0687***	0.0059**	0.0104***	0.0111***	0.0082***	0.0060**
	(0.0079)	(0.0113)	(0.0026)	(0.0026)	(0.0027)	(0.0026)	(0.0026)
AQI^2	-0.0012***	-0.0011***	-0.0002*	-0.0004***	-0.0005***	-0.0004***	-0.0003***
	(0.0003)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Weather controls		Yes	Yes	Yes	Yes	Yes	Yes
Weather controls Lags		Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood FE			Yes	Yes	Yes	Yes	Yes
Day of the week FE				Yes	Yes	Yes	Yes
Month×Year FE					Yes		
Quarter×Year FE						Yes	
Semester×Year FE							Yes
Neighborhoods	1,728	1,728	1,728	1,728	1,728	1,728	1,728
Observations	2,038,491	2,033,644	2,032,467	2,032,467	2,032,467	2,032,467	2,032,467

Notes: Regressions are at the neighborhood-day level. Daily data from January of 2017 to March of 2020. The dependent variable is number of crimes per day and neighborhood. The model is estimated using a Poisson pseudo maximum likelihood (PPML) specification. The Air Quality Index (AQI) is based on air pollution readings from the five closest monitoring stations (weighted by inverse squared distance). I include flexible weather controls and two lags of these. Please see Section 6.1 for details on these controls. Standard errors are clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1

In Figure 5, I report the associated marginal effects plot of the most demanding specification Column 5 in Table 1. It illustrates the conditional marginal effects of increasing the air quality index by one unit at different levels of the AQI, i.e., $\frac{\partial \mathbb{E}[Crimes_{i,t}|\boldsymbol{X_{i,t}}]}{\partial AQI_{i,t}}(\cdot)$. For example, when AQI is between 0 and 100, adding one unit of AQI increases crime. However, the marginal effect becomes indistinguishable from zero when the AQI reaches levels indicated as dangerous to human health, i.e., 100 and 150 units, and negative when is extremely dangerous, that is, an AQI greater than 150 units.

Finally, Figure 6 illustrates the dose-response function calculated by using a restricted cubic spline of air pollution measures with knots at the 5th, 25th, 50th, 75th, and 95th percentiles. This curve shows that the effect of the Air Quality Index on crimes, relative to having 0 units in the index, is increasing through ∼120 units. However, after 120 units are reached, the effect is sharply decreasing - i.e., the marginal effect is negative. This result supports the hypothesis that, after accounting for high levels of air pollution, crime could actually display a non-monotonic relationship with air pollution.

Figure 5: Marginal effect of increasing one unit of AQI on Crime



Notes: The figure displays the marginal effect $\frac{\partial \mathbb{E}[Crimes_{i,t}|\boldsymbol{X_{i,t}}]}{\partial AQI_{i,t}}(\cdot)$ and 95% confidence intervals of increasing one unit of the AQI on Crime for different levels of the AQI.

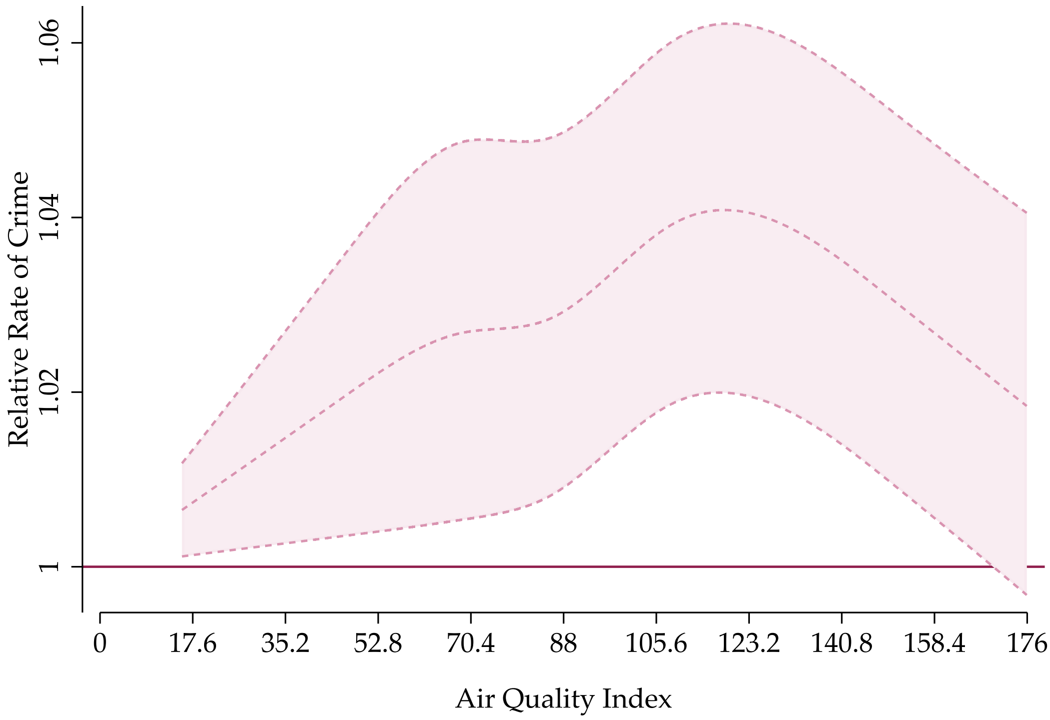
Next, given that air pollution might not be randomly generated, I implement an instrumented variable strategy to rule out any remaining time-varying confounders that could affect both air pollution and crime. Table 2 reports my main IV strategy estimates, where I use the interaction of wind speed and wind direction as an exogenous shock to air pollution.[15] The first stage estimate, in Column 1, shows that my instrument strongly predicts air pollution. The IV estimate, in Column 3, implies that 10 additional units in the AQI at the mean cause an increase in crime of 0.0216%.[16] which is only 5.37% bigger than the OLS effect of 0.0205%.[17]

[15]To address concerns about the violation of the exclusion restriction when using wind speed as part of my instrument, I add wind speed as a covariate to estimate Equation 1 and I found that after controlling for air pollution, wind speed doesn't have a direct effect on the number of crimes. See Table A.2 in the Appendix.

[16]Based on Column 3 in the Table 2 and taking into account that the mean AQI is 90.5, this value is computed as $\frac{\partial Crimes_{i,t}}{\partial AQI_{i,t}} = \frac{\beta_1}{10} + \frac{2}{100} \cdot \beta_2 \cdot AQI = \frac{(0.0818)}{10} + \frac{2}{100} \cdot (-0.0044) \cdot 90.5 = 0.0216\%$

[17]Based on Column 5 in the Table 1 and taking into account that the mean AQI is 90.5, this value is computed as $\frac{\partial Crimes_{i,t}}{\partial AQI_{i,t}} = \frac{\beta_1}{10} + \frac{2}{100} \cdot \beta_2 \cdot AQI = \frac{(0.0111)}{10} + \frac{2}{100} \cdot (-0.0005) \cdot 90.5 = 0.0205\%$

Figure 6: AQI dose-response function for crimes relative to AQI equal to zero.



Notes: This figure represents a dose-response curve between air pollution and crime. It corresponds to a cubic spline with knots at the 25th, 50th, 75th, and 95th percentiles.

7.2 Key robustness tests

Allowing for differential time trends Column 1 in Table A.3 reports the results when I include borough-specific time trends. By including these trends, I control for invariant differences between high and low-crime boroughs and for changes in aggregate time trends in crime and pollution across days. My results are robust to including these trends.

Environmental Alerts As recently shown by (Aguilar-Gómez, 2020), considering the role of environmental alert days is important because those can directly improve air quality through a mitigation strategy pushed by the government rather than by individuals. Column 2 in Table A.3 shows that my results are robust to account for the presence of environmental alerts.

Time-specific shocks: Holidays During holidays, people are more likely to change their sleeping habits, alter their commuting patterns, modify outdoor time, and even travel outside the city. Therefore, the pollution-crime relationship could look different during those days.

Table 2: Air pollution's impact on crime: Instrumental Variable model

Dependent Variable:	AQI	Number of Crimes	
	(1)	(2)	(3)
Model:	First Stage	Reduced Form	IV
Wind speed	-2.2987***	-0.0210**	
	(0.0227)	(0.0105)	
Wind Speed × Dominant Wind is in Quadrant 2	-0.1180***	0.0040	
	(0.0117)	(0.0081)	
Wind Speed × Dominant Wind is in Quadrant 3	-0.0945**	0.0057	
	(0.0127)	(0.0081)	
Wind Speed × Dominant Wind is in Quadrant 4	-0.1454***	0.0086	
	(0.0135)	(0.0087)	
AQI (10 units)			0.0818***
			(0.0161)
AQI^2			-0.0044***
			(.0009)
Weather Controls	Yes	Yes	Yes
Lags of Weather controls	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes
Day of the week FE	Yes	Yes	Yes
Month×Year FE	Yes	Yes	Yes
Neighborhoods	1,728	1,728	1,728
Observations	2,034,623	2,032,315	2,032,315
R-squared	0.6399		

Notes: Regressions are at the neighborhood-day level. Daily data from January of 2017 to March of 2020. The Air Quality Index (AQI) is based on air pollution readings from the five closest monitoring stations (weighted by inverse squared distance). I include flexible function of weather controls, and two lags of these. Please see Section 6.1 for details on these controls. Standard errors are cluster-robust over neighborhoods. *** p<0.01, ** p<0.05, * p<0.1

Hence, I include holidays as a control in my baseline specification to remove statistical noise to by-holiday variation in crime and air pollution. Column 3 in Table A.3 reports that my results are robust to that inclusion.

Varying the number of monitoring stations used to compute pollution and weather variables The number of ground-based stations used to assign a daily pollution measure to each neighborhood may affect the accuracy of my results. Thus, in column 3 in Table A.3, I show the estimated coefficients are robust to using three monitoring stations instead of five.

8 Mechanism: The role of behavioral and adaptation responses

Evidence of the underlying mechanisms for the link between air pollution and crime is essential for designing environmental and crime mitigation policies. I hypothesize that behavioral responses mediate the relationship between air pollution and crime. To examine this hypothesis, I look into the effects of different types of crimes to test whether some crimes are more responsive to air pollution than others. Table 3 reports the estimates of Equation 1 using my preferred specification. The results suggest that violent crimes, including violent property crimes (robbery), are positively and non-linearly affected by air pollution. As violent crimes are more likely to be impulsive than general crimes, behavioral responses to pollution, such as aggression, may play a role.

Table 3: Air pollution affects violent crimes but not others

			Property Crime	
Dependent Variable	Violent	Non-Violent	Robbery	Theft
	(1)	(2)	(3)	(4)
AQI (10 units)	0.0226***	0.0003	0.0281***	-0.0050
	(0.0043)	(0.0026)	(0.0059)	(0.0052)
AQI^2	-0.0010***	0.0000	-0.0012***	0.0001 2
	(0.0002)	(0.0001)	(0.0003)	(0.0002)
Weather controls and Lags	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes
Day of the week FE	Yes	Yes	Yes	Yes
Month×Year FE	Yes	Yes	Yes	Yes
Neighborhoods	1,728	1,728	1,728	1,728
Observations	2,030,875	2,028,236	1,975,640	2,008,969

Notes: Regressions are at the neighborhood-day level. Daily data from January of 2017 to March of 2020. The model is estimated using a Poisson pseudo maximum likelihood (PPML) specification. The Air Quality Index (AQI) is based on air pollution readings from the five closest monitoring stations (weighted by inverse squared distance). I include flexible controls for temperature, precipitation, relative humidity; and two lags of these weather controls. Please see Section 6.1 for details about these controls. Standard errors are cluster-robust over neighborhoods. *** p<0.01, ** p<0.05, * p<0.1

Analyzing people's behaviors or emotional states after exposure to air pollution may be useful in understanding the mechanisms that mediate these effects. One way to measure peoples' responses to air pollution is by examining their feelings. Ideally, one would survey individuals daily regarding their emotional/psychological state and then map those responses to different levels of exposure to air pollution. However, a survey like this will be extremely expensive to implement. An alternative approach is to examine what people express or say—as a proxy of emotional state—through publicly available platforms in Mexico City. This information could be used to infer how people react to poor air quality. I use daily social media posts and compute their expressed sentiment using Natural Language Processing (NLP) algorithms. Specifically, I use geolocated posts from Twitter, from January 1st, 2017 to March 24th, 2020, and score their expressed negative sentiment as described in Section 4.

To estimate the relationship between air pollution and daily negative sentiment, I estimate the following econometric specification:

$$Negative\ Sentiment_{i,t} = \mu_i + \delta_t + \beta_1 \cdot Pollution_{i,t} + \boldsymbol{X'_{i,t}}\boldsymbol{\Lambda} + \epsilon_{i,t}, \tag{5}$$

where $Pollution_{i,t}$ represents the Air Quality Index (AQI) in neighborhood i on day t, and $Negative\ Sentiment_{i,t}$ is the number of tweets expressing negative sentiment. The parameter of interest is β_1 and captures the relationship between air pollution and the expressed negative sentiment on social media. Given that weather conditions, days of the week, and months are also potentially correlated with expressed sentiment (Baylis, 2020), I include the same set of fixed effects and weather controls explained in detail in Section 6.1.

Table 4 summarizes the results and documents a positive correlation between air pollution and negative expressed sentiment. The coefficients suggest that increasing the AQI by 10 units is associated with an increase between 0.8% - 1% in the number of tweets expressing negative sentiment. The positive correlation between air pollution and negative sentiment, along with the impact of air pollution on violent crime, support the hypothesis that air pollution could induce behavioral responses and positively affect crime through the behavioral channel.

I also analyze whether people engage in avoidance behaviors to reduce their exposure

Table 4: Pollution and expressed negative sentiment

Dependent Variable:	Tweets Expressing Negative Sentiment					
	(1)	(2)	(3)	(4)	(5)	(6)
Mean of Dep. Var.	1.9649	1.9654	1.9673	1.9649	1.9654	1.9673
AQI One-Day	0.0448***	0.0587***	0.0078**			
	(0.0054)	(0.0065)	(0.0031)			
AQI Three-Days				0.0532***	0.0855***	0.0097***
				(0.0065)	(0.0091)	(0.0038)
Weather controls		Yes	Yes		Yes	Yes
Neighborhood FE			Yes			Yes
Date FE			Yes			Yes
Observations	500,735	500,583	500,077	500,735	499,102	498,598

Notes: Regressions are at the neighborhood-day level. Daily data from January of 2017 to March of 2020. The model is estimated using a Poisson pseudo maximum likelihood (PPML) specification. The Air Quality Index (AQI) is based on air pollution readings from the five closest monitoring stations (weighted by inverse squared distance). I include flexible controls for temperature, precipitation, relative humidity; and two lags of these weather controls. Please see Section 6.1 for details about these controls. Standard errors are cluster-robust over neighborhoods. *** p<0.01, ** p<0.05, * p<0.1

to air pollution, which is crucial in settings with high-pollution levels. Some common strategies to mitigate exposure to air pollution are investing in air purifiers or face masks (Ito & Zhang, 2020) and reducing time outdoors. In this paper, I explore the latter by using two proxies of how mobile people are on a given day and neighborhood: (1) the number of tweets from home and (2) the number of metro journeys. Table 5 shows that increasing the AQI by 10 units is associated with an increase between 1.1% and 1.3% in the number of tweets from home, suggesting that poor air quality may increase time indoors. To support this hypothesis, Table 6 illustrates a negative correlation between air quality and metro ridership; increasing 10 units in the AQI is associated with a decrease between 3.2% and 3.9% in the number of metro journeys. Thus, pointing to reductions in outdoor time amid poor air quality.

Adaptation strategies may be more challenging to implement for some groups than others. For example, air purifiers and facemasks could be expensive and not readily available in some areas, especially before COVID-19, imposing a financial burden on poorer communities with lower WTP for clean air. Similarly, wealthier households may be more likely to limit

Table 5: Mobility Analysis I: Pollution and Tweets from Home

Dependent Variable:	Tweets From Home					
	(1)	(2)	(3)	(4)	(5)	(6)
Mean of Dep. Var.	0.9195	0.9208	0.9300	0.9195	0.9208	0.9300
AQI One-Day	0.0634***	0.0855***	0.0103**			
	(0.0069)	(0.0095)	(0.0042)			
AQI Three-Days				0.0737***	0.1205***	0.0130***
				(0.0080)	(0.0120)	(0.0056)
Weather controls		Yes	Yes		Yes	Yes
Neighborhood FE			Yes			Yes
Date FE			Yes			Yes
Observations	500,735	500,005	495,045	500,735	497,552	491,516

Notes: Regressions are at the neighborhood-day level. Daily data from January of 2017 to March of 2020. The model is estimated using a Poisson pseudo maximum likelihood (PPML) specification. The Air Quality Index (AQI) is based on air pollution readings from the five closest monitoring stations (weighted by inverse squared distance). I include flexible controls for temperature, precipitation, relative humidity; and two lags of these weather controls. Please see Section 6.1 for details about these controls. Standard errors are cluster-robust over neighborhoods. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Mobility Analysis II: Pollution and Metro Journeys

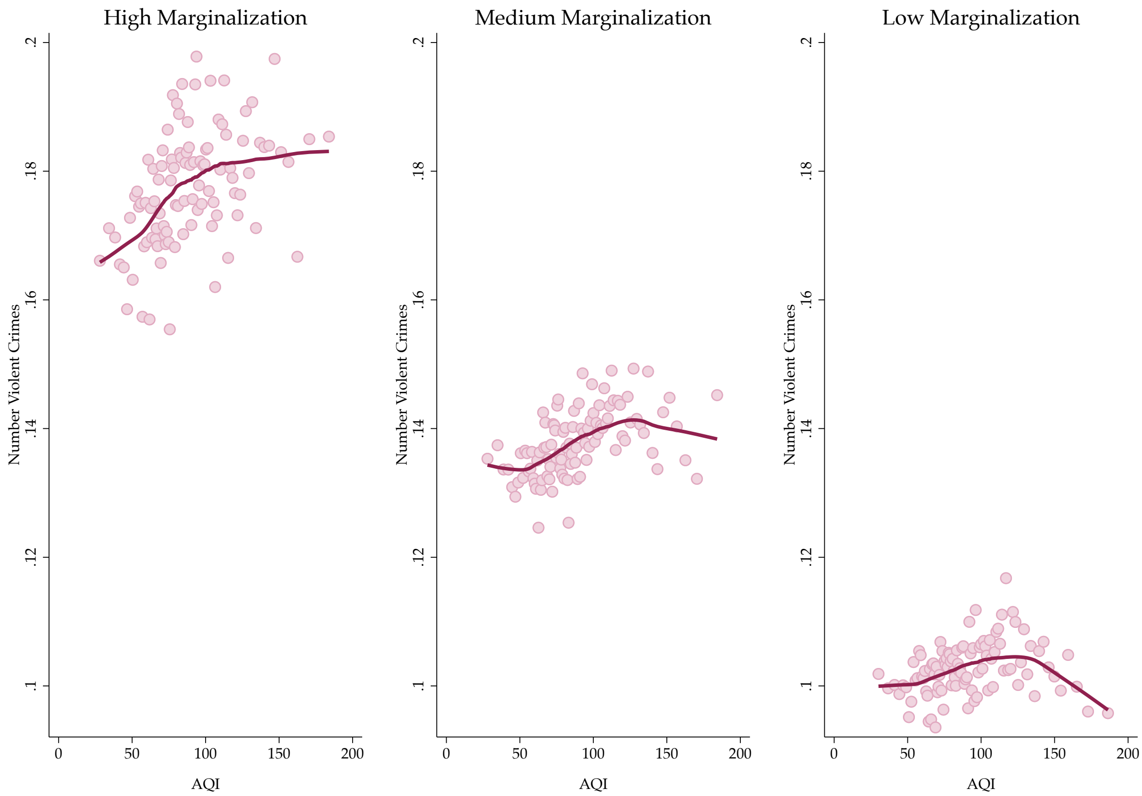
Dependent Variable:	Number of Metro Journeys per Day					
	(1)	(2)	(3)	(4)	(5)	(6)
Mean of Dep. Var.	23,871.70	23,870.70	24,032.89	23,871.7	24,918.14	24,032.89
AQI One-Day	-0.0078**	-0.0085*	-0.0319**			
	(0.0032)	(0.0045)	(0.0137)			
AQI Three-Days				-0.0099**	-0.0120**	-0.0386**
				(0.0039)	(0.0054)	(0.0164)
Weather controls		Yes	Yes		Yes	Yes
Date FE			Yes			Yes
Observations	166,040	165,958	164,838	166,040	165,958	164,838

Notes: Regressions are at the neighborhood-day level. Daily data from January of 2017 to March of 2020 for those neighborhoods with at least one metro station. The model is estimated using a Poisson pseudo maximum likelihood (PPML) specification. The Air Quality Index (AQI) is based on air pollution readings from the five closest monitoring stations (weighted by inverse squared distance). I include flexible controls for temperature, precipitation, relative humidity; and two lags of these weather controls. Please see Section 6.1 for details about these controls. Standard errors are cluster-robust over neighborhoods. *** p<0.01, ** p<0.05, * p<0.1

their time outdoors when pollution is high since they are more likely to have jobs that can be performed indoors (Hatayama et al., 2020). Thus, the responses to air pollution may differ across socioeconomic groups, potentially affecting adaptation responses.

I examine whether the relationship between air pollution and violent crimes differs across neighborhoods' socioeconomic groups—which I measure using the degree of marginalization as computed by Mexico City's government. The degree of marginalization classifies neighborhoods into five categories considering—besides income—variables such as access to public goods and sanitation infrastructure, poverty, urban decay, housing quality, and urban safety.

Figure 7: The relationship of air pollution and crime by degree of marginalization



Notes: These figures show the relationship between air pollution and crime by the Degree of Marginalization. The Degree of Marginalization classifies neighborhoods into five categories. Category five means a neighborhood is highly marginalized, and category one means that it is low marginalized. High Marginalization includes category 5; Medium Marginalization combines categories 3 and 4; and Low Marginalization combines categories 1 and 2.

Figure 7 reveals that the degree of marginalization shapes the responses to air pollution. For example, being in low marginalized neighborhoods—and, therefore, with high socioeconomic status—renders the relationship between air pollution and crime non-monotonic with a peak point around 120 units in the AQI. This result suggests that potential adaptation responses may be in place in more affluent neighborhoods. In contrast, being in a highly marginalized neighborhood suppose an increasing response of crime to air pollution, even when the concentrations are cripplingly high. Figure 7 also illustrates that although the number of violent crimes is higher in more marginalized neighborhoods, the levels of air pollution do not differ much across levels of marginalization.

9 Conclusion

This paper provides the first systematic empirical evidence of non-linearities in the relationship between air pollution and crime and, more importantly, the mechanisms that mediate this relationship.

My results reveal an inflection point after which marginal changes in air pollution negatively affect crime. I argue that these non-linearities result from two opposite forces interacting when high pollution levels are reached. On one side, violent crimes are more responsive to air pollution than other crimes, which supports the idea that air pollution might lead to behavioral responses such as aggressiveness and self-control issues. Besides, my results on social media's expressed sentiment reinforce the behavioral explanation implying that poor air quality may lead to lower individuals' emotional state. On the other side, people seem to engage in adaptation strategies to mitigate the effects of air pollution, especially when high pollution levels are reached. In particular, individuals seem to alter their mobility patterns and stay indoors, which would reduce the number of individuals on the streets and, therefore, negatively affect crime.

These results are consistent across multiple identification strategies that rely on 1) highly dimensional fixed-effect models, 2) the non-parametric estimation of a dose-response function, and 3) an instrumental variable approach that employs wind speed and wind direction as instruments for air pollution. Moreover, those are robust to the inclusion of borough-specific time trends and to the presence of holidays and environmental alerts.

My findings provide important insights for developing countries where pollution and crime are usually high.

First, replication in diverse contexts is critical for external validity. By studying the pollution-crime relationship in a city with pollution levels more typical of many mega-cities in the developing world, I show that defensive behaviors can vary markedly depending on the intensity of pollution concentrations. Hence, extrapolating results from cities in industrialized countries may render those estimates non-externally valid in high-polluted settings like Mexico City.

Second, more research is needed to identify and quantify the potential behavioral responses to air pollution. For example, my results about changes in individuals' emotional states reveal that there are less noticeable impacts of air pollution that may affect well-being and are not currently considered in the design of pollution mitigation policies. Conversely, avoidance behaviors may be costlier to implement by certain groups. Yet, we still haven't determined the causes of those differential costs.

Finally, given that only wealthier places in Mexico City seem to engage in adaptation strategies, air pollution exposure is likely to be heterogeneous. This unequal take-up of remediation behaviors against poor air quality raises significant environmental justice concerns and invites policymakers to consider them in implementing environmental and crime mitigation policies. Although the optimal design of environmental policies to reduce air pollution in developing countries is out of the scope of this paper is a fruitful avenue for future research.

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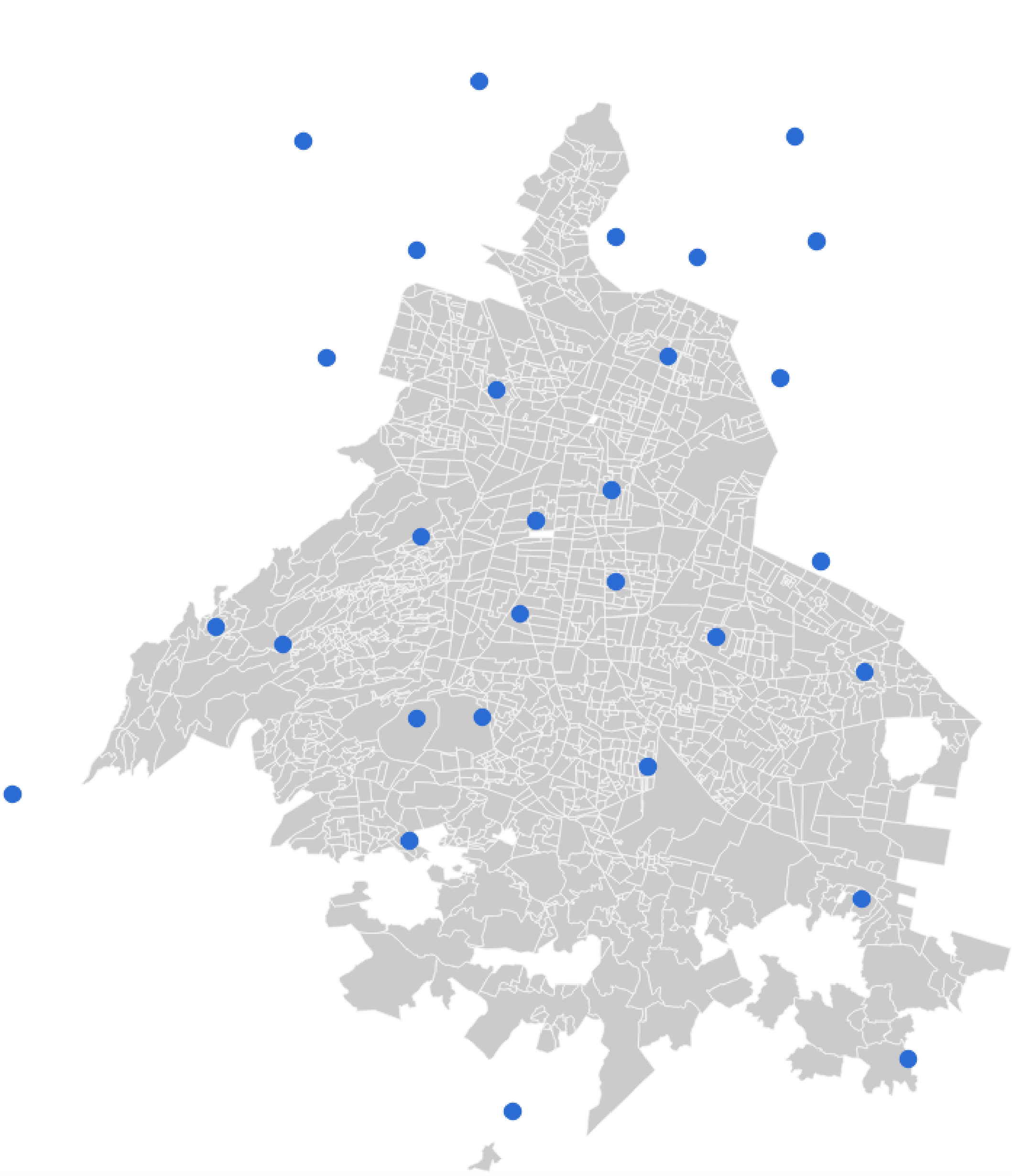
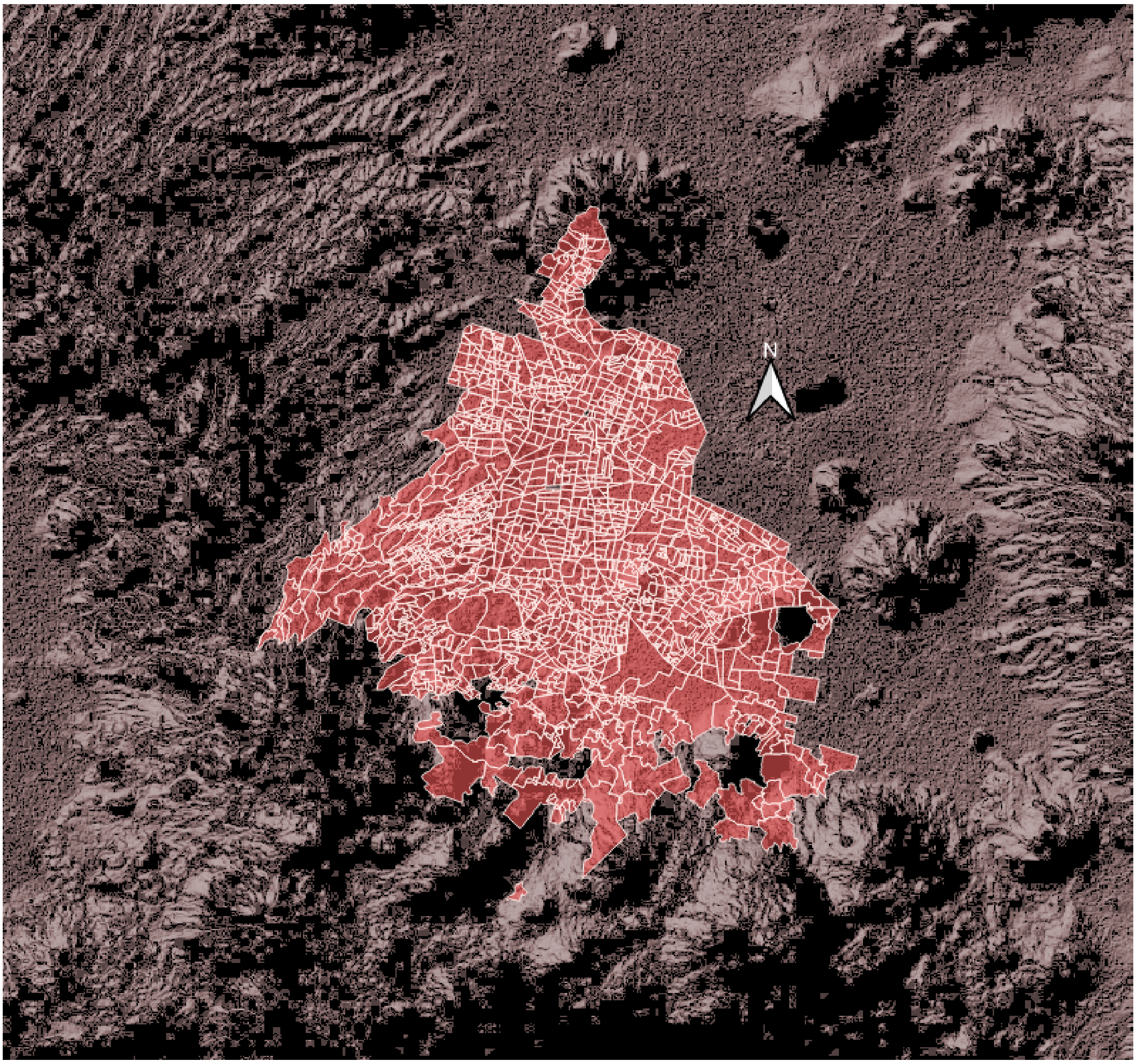
A Appendix for Online Publication

Figure A.1: Geographical distribution of monitoring stations in Mexico City



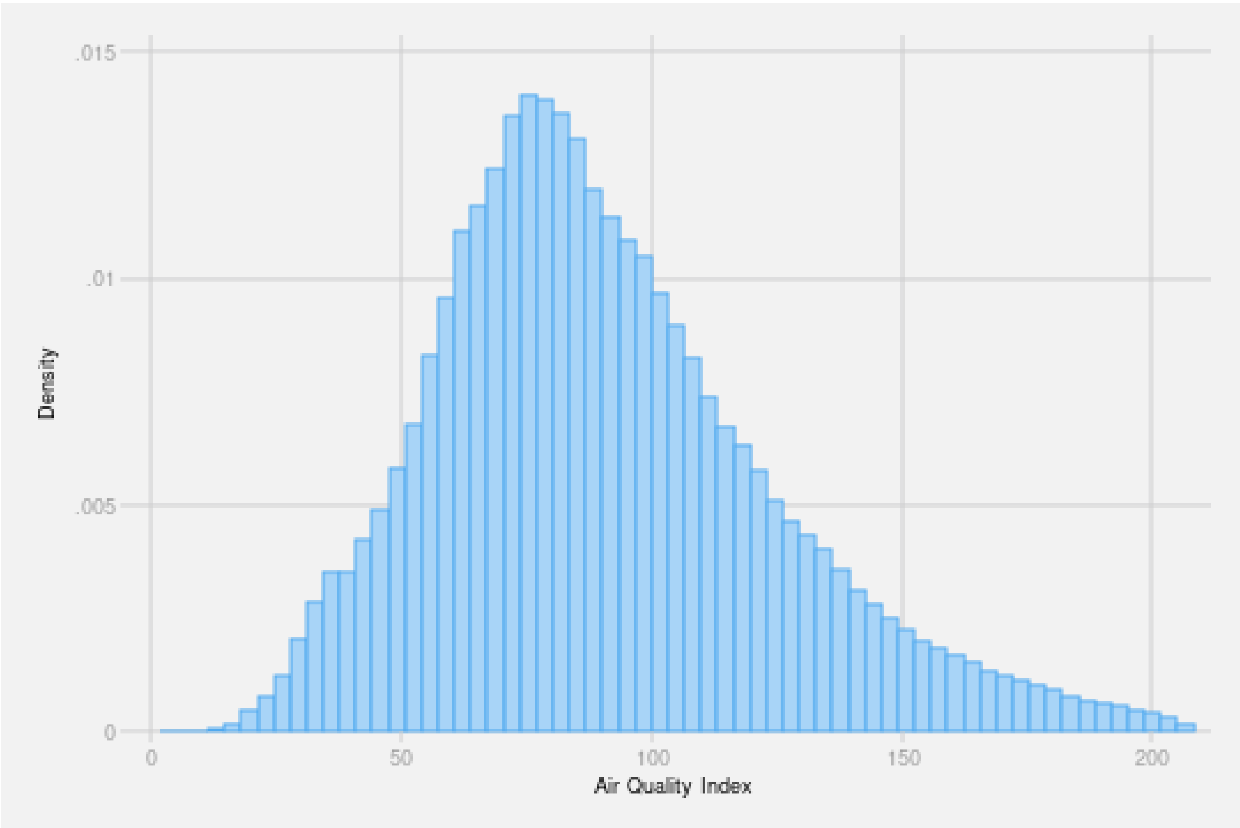
Notes: This figure presents a map with the neighborhoods (in light gray) and the location of meteorological stations (in blue) in Mexico City.

Figure A.2: Topographic Terrain around Mexico City



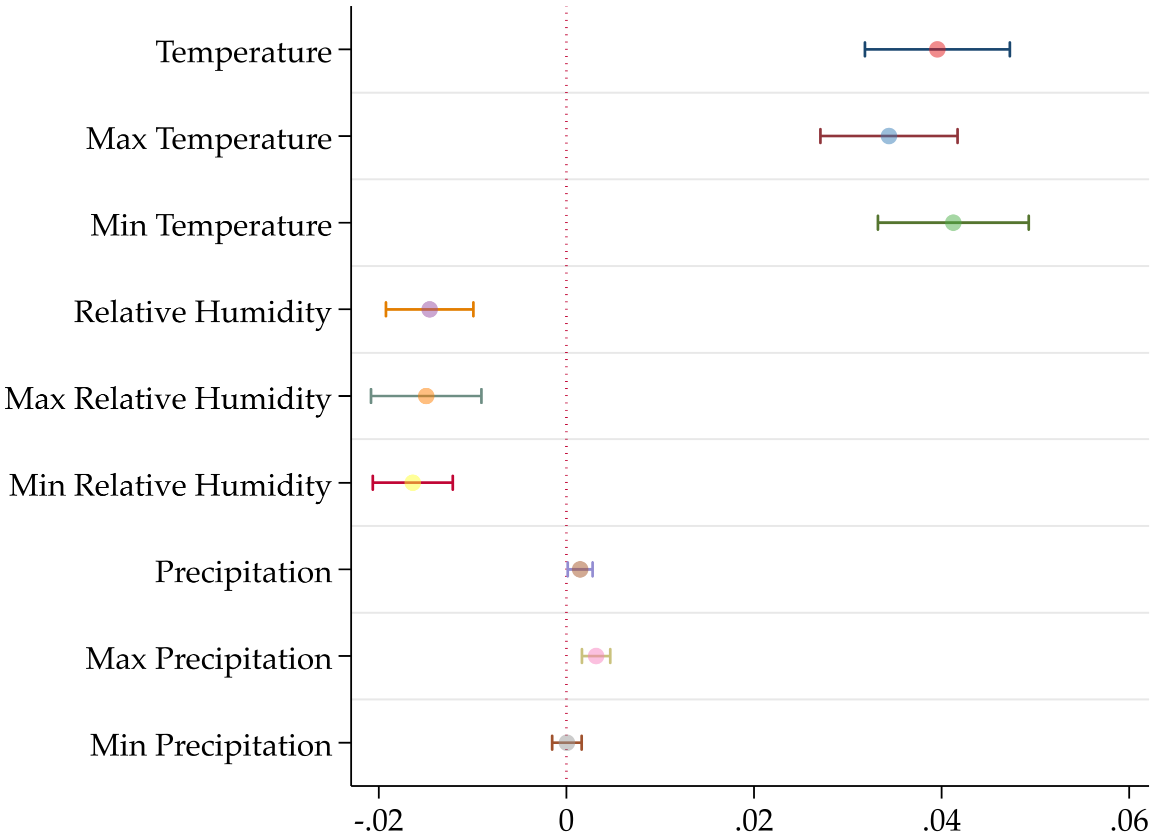
Notes: This figure presents the map of neighborhoods and the elevation raster for the Mexico City area.

Figure A.3: Histogram of the Air Quality Index in Mexico City



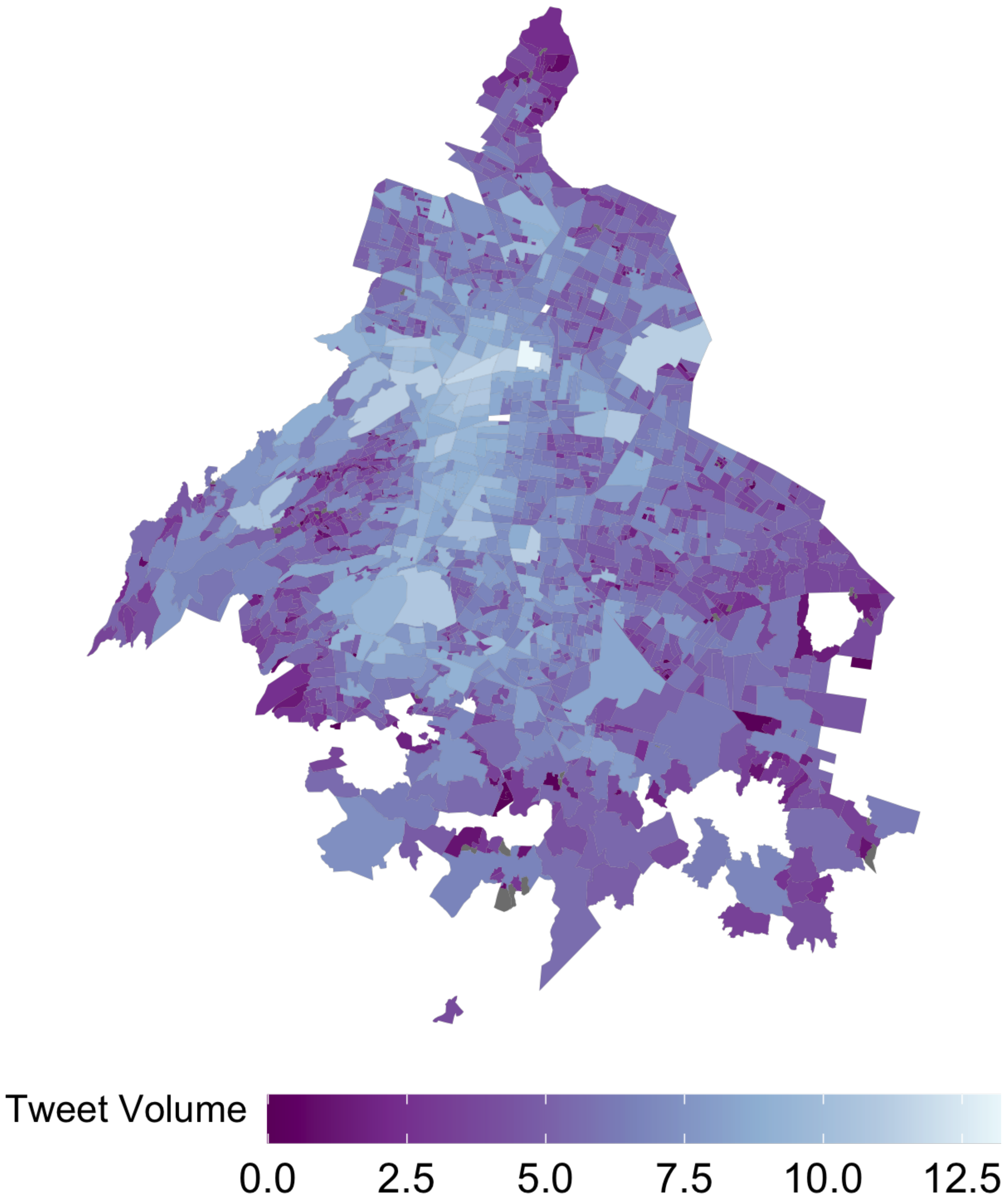
Notes: This figure presents the empirical distribution of the Air Quality Index in Mexico City during the sample period from January 2017 to March 2020.

Figure A.4: Crime is highly correlated with weather variables



Notes: This figure presents the estimated coefficients and 95% confidence intervals of bi-variate regressions between the number of crimes and the weather variables listed in the y-axis using data at the day-neighborhood level.

Figure A.5: Logarithm of the number of tweets in sample



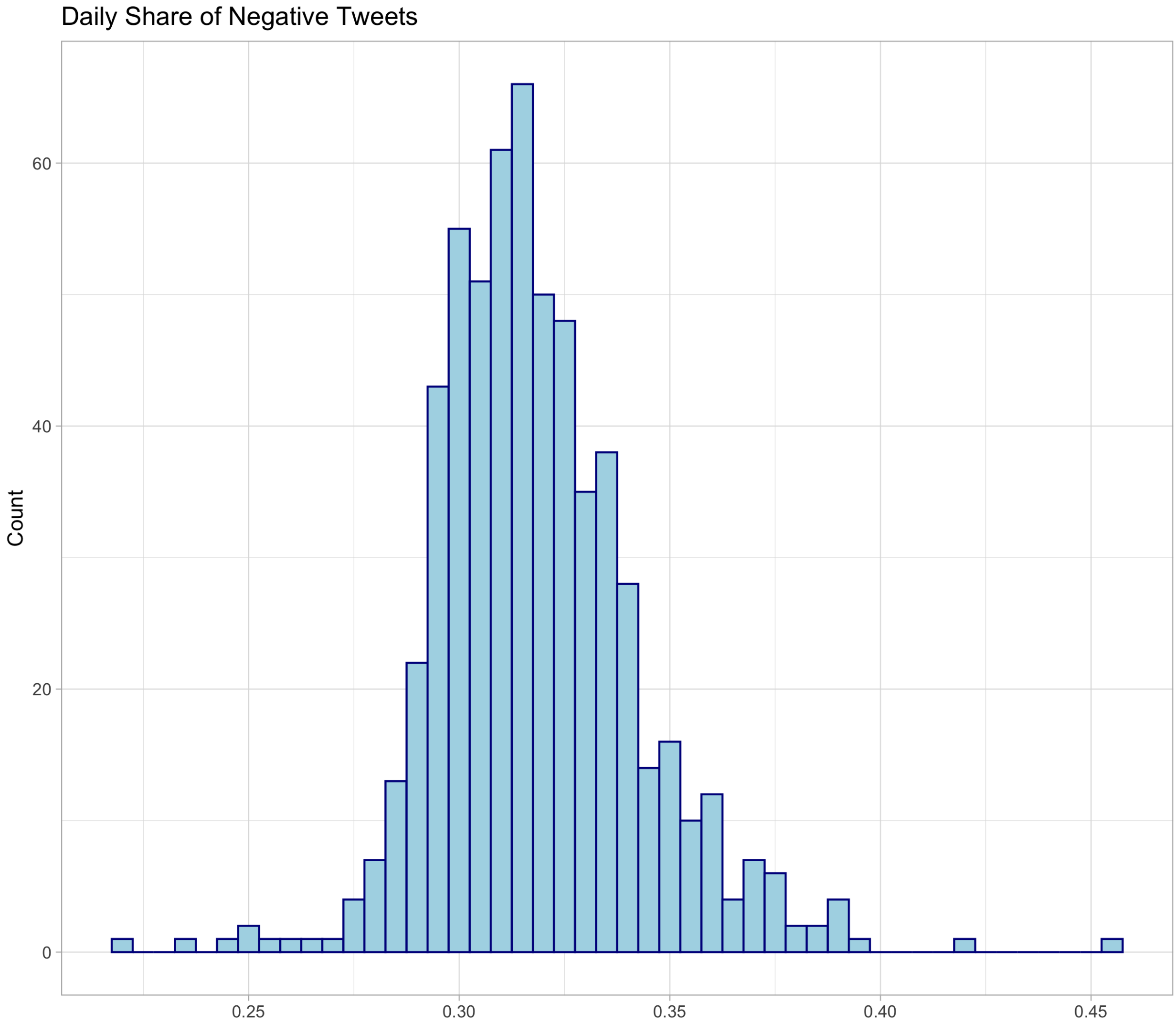
Notes: The pixel shading represents the Log (base 10) of the count of tweets in my sample aggregated it at the neighborhood level. Tweets from January 2017 to March 2020.

Figure A.6: Result of the pre-processing applied on a sample tweet

Original Tweet	Processed Tweet	P[Positive]	P[Neutral]	P[Negative]	Sentiment
Con la puchunga 👌🏻😁❤️ Que mejor compañía después del trabajo (@ Santa Clara in Mexico City, Distrito Federal) https://t.co/A6ZlXWsqXm	Con la puchunga emoji señal de aprobación con la mano tono de piel claro emoji emoji cara radiante con ojos sonrientes emoji Que mejor compañía después del trabajo (@usuario Santa Clara in Mexico City, Distrito Federal) url	0.696	0.298	0.006	**Positive**
BUENOS DIAS!!! . . Excelente semana para todos!!! 👍🏼 🌻 Hoy tenemos muchas cosas que planear!! 🥰 Pronto tendremos: •Juntas de fin de curso •Storytime y conferencia sorpresa. •Cursos de verano "Fun Weeks" . . . .… https://t.co/gLD0hv7n27	BUENOS DIAS!!! . . Excelente semana para todos!!! emoji pulgar hacia arriba tono de piel claro medio emoji emoji girasol emoji Hoy tenemos muchas cosas que planear!! emoji cara sonriendo con corazones emoji Pronto tendremos: Juntas de fin de curso Storytime y conferencia sorpresa. Cursos de verano "Fun Weeks" . . . . ur	0.913	0.086	0.01	**Positive**
Tardando mas de la cuenta 😡 (@ Secretaria De Economia in Ciudad de México, DF) https://t.co/pI0Z3WkpD6	Tardando mas de la cuenta emoji cara cabreada emoji (@usuario Secretaria De Economia in Ciudad de México, DF) url	0.001	0.003	0.996	**Negative**
Solo 😞 (@ Starbucks Lomas Estrella) https://t.co/L3sSGM4SoO	Solo emoji cara decepcionada emoji (@usuario Starbucks Lomas Estrella) url	0.001	0.021	0.978	**Negative**

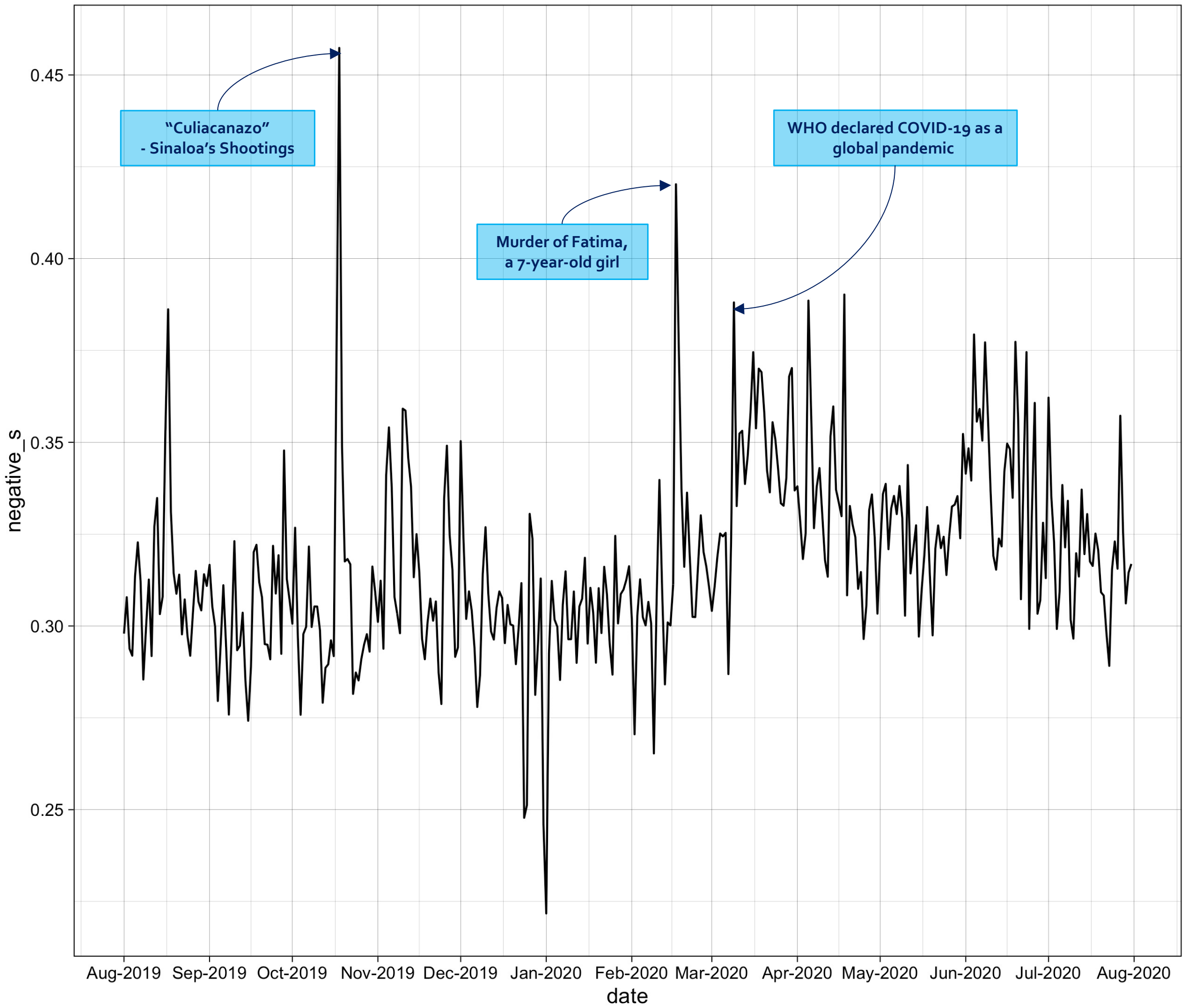
Notes: This figure shows a sample of the original and the processed or cleaned tweets used as input to perform sentiment analysis. The pre-processing is done using a function of the toolkit *pysentimiento*. The function converts emojis into descriptive words, normalizes laughs, and removes URLs, hashtags, punctuation, user handles, and repeated words up to three occurrences. This figure also shows the vector of sentiment scores of those tweets and the sentiment assigned to each tweet based on the scores.

Figure A.7: Distribution of the Daily Share of Tweets with Negative Sentiment



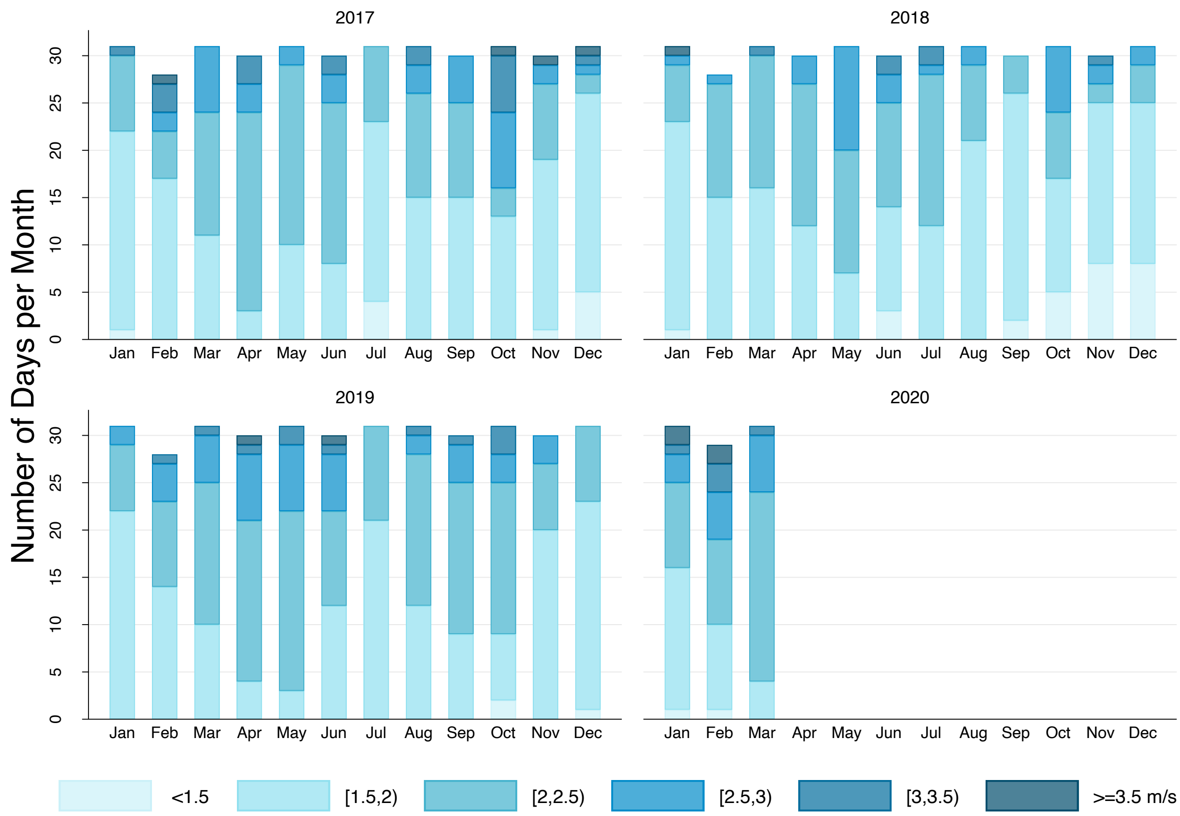
Notes: Data from January 2017 to March 2020. This figure shows the share of daily negative sentiment in the tweets in my sample. The expressed sentiment is computed using Natural Language Processing algorithms that interpret and classify emotion with text data.

Figure A.8: Daily Share of Negative Sentiment



Notes: Daily share of negative sentiment over time in the tweets from my sample. This figure shows that the peaks of negative sentiment coincide with the important negative events. The expressed sentiment is computed using Natural Language Processing algorithms that interpret and classify emotion with text data.

Figure A.9: Average Wind Speed by Category and Month



Notes: Number of days per month that the average wind speed lies in one of the 6 categories. Wind Speed in meters per second (m/s).

Table A.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Total Crime	0.349	0.810	0	150	2,207,933
Violent	0.128	0.395	0	20	2,207,933
Non-Violent	0.221	0.637	0	149	2,207,933
Property Crime	0.098	0.353	0	20	2,207,933
Robbery	0.060	0.262	0	20	2,207,933
Theft	0.086	0.336	0	20	2,207,933
Air Quality Index (AQI)	90.508	34.034	1.655	208.335	2,207,933
3 Day Mean AQI	90.548	31.135	3.341	207.27	2,207,933
PM2.5 ($\mu g/m^3$)	22.486	10.06	1.000	130.867	2,194,172
PM10 ($\mu g/m^3$)	42.052	18.336	1.000	228.917	2,174,515
Ozone (ppb)	31.71	11.089	1.024	107.899	2,207,933
Carbon Monoxide (ppm)	0.47	0.23	0.015	3.278	2,207,352
Nitrogen Dioxide (ppb)	24.808	8.862	1.421	109.429	2,206,018
Sulfur Dioxide (ppb)	3.828	4.218	0.000	64.782	2,207,801
Wind Speed (m/s)	2.109	0.522	0.501	7.713	2,207,689
Temperature (Celsius)	17.39	2.558	2.415	24.830	2,207,879
Relative Humidity (%)	52.237	13.882	9.125	97.925	2,207,879
Mean Rain (mm)	1.395	2.391	0.000	15.000	2,207,933
Number of tweets	6.808	26.789	1.000	1046.000	500,735
Number of negative tweets	1.965	5.767	0.000	282.000	500,735
Number of neutral tweets	3.515	15.444	0.000	670.000	500,735
Number of positive tweets	1.328	7.015	0.000	348.000	500,735

Notes: Observations are at the neighborhood-day level. Data from January 1st of 2017 to March 31st of 2020.

Table A.2: Adding Wind Speed as a Control Variable

Dependent Variable:	Number of Crimes	
	(1)	(2)
AQI	0.0111***	0.0112***
	(0.0027)	(0.0028)
AQI^2	-0.0005***	-0.0005***
	(0.0001)	(0.0001)
Wind Speed		0.0010
		(0.0043)
Weather Controls	Yes	Yes
Lags of Weather controls	Yes	Yes
Neighborhood FE	Yes	Yes
Day of the week FE	Yes	Yes
Month$\times$Year FE	Yes	Yes
Neighborhoods	1728	1728
Observations	2,032,467	2,032,277

Notes: Regressions are at the neighborhood-day level. Daily data from January of 2017 to March of 2020. Standard errors are cluster-robust over neighborhoods. *** p<0.01, ** p<0.05, * p<0.1

Table A.3: Air Pollution's Impact on Crime: Robustness

Dependent Variable:	Number of Crimes			
	(1)	(2)	(3)	(4)
AQI	0.0109***	0.0103***	0.0096***	
	(0.0027)	(0.0028)	(0.0027)	
AQI^2	-0.0005***	-0.0004***	-0.0004***	
	(0.0001)	(0.0001)	(0.0001)	
AQI (IDW using 3 stations)				0.0097***
				(0.0025)
AQI^2 (IDW using 3 stations)				-0.0004***
				(0.0001)
Boroughs Time Trend	Yes			
Environmental Alerts		Yes		
Holidays			Yes	
Observations	2,032,467	2,032,467	2,032,467	2,031,967

Notes: Regressions are at the neighborhood-day level. Daily data from January of 2017 to March of 2020. The Air Quality Index (AQI) is based on air pollution readings from the five (three) closest monitoring stations (weighted by inverse squared distance). I include flexible function of weather controls, and two lags of these. Standard errors are cluster-robust over neighborhoods. *** p<0.01, ** p<0.05, * p<0.1