Adaptation and mitigation of pollution: evidence from air quality warnings

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Abstract

Standard economic analyses of environmental policy focus on either reducing pollution externalities through mitigation or reducing the harms from exposure by encouraging adaptation. In practice, these issues are both critical, particularly when looking at the health effects of local air pollutants, which can be acute, and policymakers often pair information provision with short and long-run mitigation actions. This paper studies one widely used example of such a policy—air quality alerts. I explore whether, in the context of the Mexico City air quality alert program, information policy is more effective when paired with mitigation. I find that the policy did not improve air quality or health outcomes until the mitigation component, which limited transport emissions, was introduced. I also use sensor-level traffic data, geo-tagged accident reports, and search data as a measure of awareness of the policy to unveil the mechanisms through which considerable short-run improvements in air quality and health are achieved after issuing an alert. I find that the alert reduces car usage even before the driving restrictions enter into place, suggesting that, due to an increased awareness of pollution, people reduce their trips.

Keywords: Pollution control, public health, driving restrictions
JEL Codes: Q50, Q52, Q58, I10, I18

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1 Introduction

Standard economic analyses of environmental policy focus on either reducing externalities through mitigation or reducing the harms from externalities by encouraging adaptation. The former aims at reducing human activities' impacts on the environment, while the latter seeks to minimize damages at a given level of environmental degradation through protective behavior. Limiting emissions of hazardous particles, for example, is a classic mitigation strategy, and information provision is a common response that tries to facilitate adaptation. In practice, these issues are both critical, particularly when looking at the health effects of local air pollutants, which can be acute. In response to real-world complexity and the necessity of protecting the population from very polluted days, policymakers have taken a multi-pronged approach that pairs information provision with short and long-run mitigation actions. This paper studies one widely used example of such a policy: air quality alerts.

Exposure to air pollution has substantial negative impacts on human health, even within a time horizon of days or even hours after exposure (Schlenker and Walker, 2015; Deryugina et al., 2019; Samoli et al., 2006; Mills et al., 2015). Consequently, while navigating politically complex long-run solutions to improve air quality, city governments worldwide have increasingly adopted air quality warnings as a measure to reduce the health impacts of very polluted days. These programs are especially relevant in regions where extreme pollution levels accompany rapid and often disorganized urbanization. Reduced local governments' capacity often translates into high marginal costs of environmental quality improvements (Greenstone and Jack, 2015). High abatement costs paired with low marginal costs of self-protection can lead policymakers to prefer approaches that provide incentives to invest in self-protection rather than investing in better environmental quality. India and China have recently invested in developing robust pollution monitoring systems that help inform the population when they should take self-protection measures. In fact, today roughly 40% of the world's population lives in a country that has air quality alert systems in its largest cities.

When pollution surpasses a certain threshold, air quality warnings inform the population about the risks of going outdoors and encourage them to reduce their exposure to hazardous air quality. Recently, policymakers have introduced additional restrictions when air quality is poor. These temporary restrictions seek to achieve very short run mitigation of outdoor air pollutants by limiting industry and transport emissions. Decision-makers face a double bind if they want to implement short-run mitigation and information policies. On the one hand, they seek to provide information to help people reduce the harm they experience from environmental extremes (Neidell, 2009, 2010; Shrader, 2020). On the other hand, providing information can undermine mitigation efforts and vice-versa. Research has quantified offsetting mechanisms between these two policy goals, showing that protective measures against climate change can in fact increase emissions. Air conditioning is a prime example of adaptation to climate change that also contributes to its worsening. In a warming world, this technology has been key in reducing the relationship between extreme temperatures and mortality (Barreca et al., 2016). However, the residential sector alone is set to account for an over 0.5° C increase in global temperatures by 2100, with comfort cooling being a primary source of emissions (Sachar et al., 2018). Mitigation measures can also increase exposure to pollution (Knittel et al., 2016; Che et al., 2016). For instance, if driving restrictions force people to walk more and use more public transportation, they might end up with more exposure to pollution since these modes of transportation are more exposure-intensive than driving (Che et al., 2016). [1]

In this paper, I explore whether these trade-offs exist between mitigation and adaptation to air pollution. To answer this question, I study a program that, before 2016, provided only information about high pollution levels in the form of alerts. In 2016, the policy was changed: warnings were issued at the same pollution levels, but now mitigation measures were also undertaken; notably, driving restrictions were to be put in place every time an alert was issued. The context of this study, the Mexico City Environmental Alerts Program (PCAA [2] for its Spanish acronym), is uniquely suited to answer the research question: I leverage this policy change and exploit the outstanding data availability to look closely at the interactions between adaptation and mitigation. I use hospital-level health outcomes matched to monitor-level pollution and weather data to estimate the pollution and health effects of the policy. I also use a novel data set that contains car counts and speed measurements from more than 300 traffic sensors installed throughout the city, geo-

[1] On the specific role of information on mitigation efforts, research has found that while communicating the policy is an intrinsic part of implementation, if information allows people to anticipate and circumvent an environmental policy, it can strongly undermine it. Examples of this paradox range from vehicle emission standards (Rittenhouse and Zaragoza-Watkins, 2018) to marine conservation policy (McDermott et al., 2019).

[2] *Programa de Contingencias Ambientales y Atmosféricas*

tagged accident reports, and an awareness measure constructed using social media scraped data to unveil the mechanisms through which their effects operate.

The threshold to declare a PCAA alert —155 parts per billion of ozone— is very high relative to the distribution, so only a handful of them are issued every year. Alert days are exceptional in terms of pollution patterns, with mean reversion expected to happen after a local maximum in pollution. Hence, they cannot be directly compared to other random days throughout the year. To solve this problem, I employ the synthetic control method (Abadie et al., 2010, 2015) to generate a control group composed of days with similar pollution trajectories, but that barely missed the PCAA threshold. I match alert days to a weighted average of potential controls using expected pollution as a selection criterion, driven by meteorological conditions and past pollution levels.

I find that before the 2016 reform, when there was only an adaptation component, the policy does not improve air quality. However, the program has strong same-day effects after 2016, when the mitigation component was introduced: a cumulative reduction of more than seven times the hourly standard deviation of the pollution index. The driving restrictions only operate between 5 am and 10 pm, and the effect estimates reflect these hourly patterns. Pollution bounces back on the second day after the alert, likely driven by the postponed trips in response to restrictions. Despite the night-time and second-day increases in pollution, the net cumulative exposure is reduced by 2.5 standard deviations. The results are driven by reductions in NO2 and CO, while PM10 and SO2 remain mostly unaffected by the policy.

To estimate the policy impacts on health, I match each hospital in the city to the three closest weather monitoring stations to obtain a daily measure of pollution in each hospital's catchment area. Then, to control for pollution unaffected by the PCAA alerts, I use wind speed and wind direction as an instrument for pollution. The rationale behind this strategy is that by controlling for predicted pollution, I can quantify the effects of mitigation (policy-driven deviations from predicted pollution) and adaptation (protective measures when notified that air quality can be hazardous). I find that the policy's effect on ER visits happens exclusively after the 2016 reform, suggesting that the mitigation component is critical in achieving public health benefits. For a typical alert issued after the 2016 reform, there is a decrease of 8% in respiratory ER visits. The impacts are driven by reductions in ER visits by children and the elderly, who experience an 11.4% decrease in ER admissions. The effects are most substantial for asthma, with a 57% reduction. The positive effects last for several days, with 50.2 respiratory admissions reduction over the week.

The policy is successful in cutting down emissions by reducing the number of car trips made. Using average vehicle speed and car counts as complementary road traffic measures, I find that car usage decreases significantly after an alert is issued. The average speed in the city increases up to 5%. Car counts decrease by up to 18%. Emptier streets also have significant co-benefits: there is a decrease of up to 18% in the number of accidents per hour. The total reduction in road accidents in the city in PCAA days is 51.2.

Finally, I use search trends data to answer why the paired policy works so much better than the pre-2016 information policy alone. While there was no change in awareness or interest in these topics when an alert was issued in the pre-reform period, I show that the mitigation component of the alert that entered in 2016 made the warnings more salient for people, generating an increased interest - measured using Google searches- in both the PCAA program and air pollution in general. This increased awareness is a potential driver of the reductions in car usage that happen on the day the alert is issued, even when driving restrictions do not enter into play until the next morning. My findings suggest that people reduce their discretionary trips in response to information about pollution, but only after the alert gains enough salience.

This paper contributes to our understanding of a central tension in environmental policy: balancing the marginal damage of pollution with the marginal abatement costs. Because of the several potential trade-offs, more research is needed on the interaction of adaptation and mitigation policies. Previous literature has shown that information can be counter-productive if it generates preemptive behaviors (e.g.over-fishing or buying dirty vehicles before the restrictions enter in place). Driving restrictions in Mexico are a prime example: Davis (2008) found that after a permanent driving restrictions program was implemented in Mexico City, most people bought a second cheaper -and dirtier- car, rendering the policy ineffective in the long run. My results contrast with this literature: I show that the additional driving restrictions implemented during a PCAA alert effectively reduce the number of trips. My results imply that the mitigation component is crucial to achieve the health effects of the PCAA alerts, reinforcing the salience of the policy for people. By looking at temporary driving restrictions, I find contrasting results with the majority of the literature, which has found air quality warnings to be ineffective in reducing air pollution (Davis, 2008; Gallego et al., 2013; Zhang et al., 2017).[3]

My findings also contribute to the information and protective behavior literature and, more specifically, to the air quality warnings literature, which is focused on the US and Europe, has mostly overlooked programs that include mitigation, and has found mixed results on their effectiveness (See Neidell (2009); Welch et al. (2005); Saberian et al. (2017) and Tribby et al. (2013)).

Another strength of this paper is the vast and disaggregated data set that I compiled, using half a dozen public and previously unavailable data sources.[4] This is the first paper to use this traffic data set for Mexico City to the best of my knowledge. Moreover, other studies on air quality warnings do not link them directly to health outcomes, which requires matching hospitals and their catchment areas with air monitoring stations that I do to quantify exposure to pollution.

Finally, I contribute to the quasi-experimental literature in economics on the health effects of air pollution.[5] I show that the distribution of high pollution levels over time, rather than merely their aggregate amount, may be essential in determining the health damages generated from it. So, generating discontinuities in exceptionally high pollution levels may improve health outcomes, even if emissions aggregated over a longer time interval are only modestly affected.

The rest of the paper proceeds as follows. Section 2 outlines in detail the contributions of this paper to the literature. Section 3 describes the PCAA program and the typical progress of an air quality alert. Section 4 presents the data sources with descriptive statistics. Section 5 presents the methodology. Section 6 presents the effects of air quality warnings on pollution. Section 7 presents the effects of air quality warnings on hospital admissions. Section 8 presents evidence on the mechanisms behind the pollution and health effects of

[3] The literature has found mixed results for China (Lin et al., 2011; Viard and Fu, 2015)

[4] The car counts and speed data sets were obtained through direct data requests made through the INFOMEX system, an electronic service managed by the National Institute for Access to Information.

[5] Most papers in this literature look at infant mortality. See Chay et al. (2003); Currie and Neidell (2005); Currie et al. (2009b); Chen et al. (2013); Deschenes et al. (2017); Schlenker and Walker (2015) and Deryugina et al. (2019) for some exceptions.

the policy. Section 9 concludes.

2 Previous work and contribution

There are three strands of literature that this work contributes to: first, the quasi-experimental literature in economics on the health effects of air pollution; second, the literature on information and avoidance behavior; and finally, the nascent literature on the tensions between mitigation and adaptation. In this section, I briefly describe previous work on each of these areas and state the contributions of this paper.

The effects of air pollution on mortality have been robustly documented in economics. Children and the elderly are the most vulnerable groups (Currie and Neidell, 2005; Arceo et al., 2016). Specifically for Mexico, Foster et al. (2009) exploit satellite-based measures of aerosol optical depth as a measure of particulate matter to examine the effect of a voluntary air – quality regulation on infant health in Mexico. Their estimates indicate that a 1 percent increase in AOD[6] results in a 4.4 percent increase in respiratory mortality. Pollution also has an impact on a variety of outcomes, from morbidity, hospital admissions and health expenses, (Chay et al., 2003; Deryugina et al., 2019), to human capital accumulation (Currie et al., 2009a; Graff Zivin and Neidell, 2013; Lavy et al., 2012) and labor supply (Hanna and Oliva, 2015) and productivity (Chang et al., 2016; Graff Zivin and Neidell, 2012).

The public health literature has documented how very short-run changes in air quality also affect general and cause-specific morbidity and mortality. These variables respond even to same-day changes. This is, pollution has acute effects on human health. Short-term exposure to ambient NO2 has adverse effects on pulmonary function, particularly in asthmatics, and may increase airway allergic inflammatory reactions, hospital admissions, and mortality (Samoli et al., 2006). In a systematic review conducted by Mills et al. (2015), a 10 μg/m3 increase in the daily NO2 mean was associated with increases in all-cause, cardiovascular and respiratory mortality (0.71% , 0.88% and 1.09%, respectively), and with hospital admissions for respiratory (0.57%) and cardiovascular (0.66%) diseases. Similarly, both acute and chronic exposure to carbon monoxide are associated with increased risk for

[6]Aerosol optical depth (AOD) is a measure of the extinction of the solar beam by dust and haze. In other words, particles in the atmosphere (dust, smoke, pollution) can block sunlight by absorbing or by scattering light. AOD tells us how much direct sunlight is prevented from reaching the ground by these aerosol particles.

adverse cardiopulmonary events, including death (Chen et al., 2007). Knittel et al. (2016) show that even at current levels, CO has large marginal effects on weekly infant mortality rates, especially for premature or low birth weight infants.

The acute effects of pollution and their costs for health systems have been, to a lesser extent, addressed in the economics literature. Deryugina et al. (2019) finds substantial effects of acute fine particulate matter exposure on mortality, health care use, and medical costs among the US elderly using an IV approach in which they instrument for air pollution using changes in local wind direction. These effects manifest themselves within a three-day window. Similarly, Schlenker and Walker (2015) use daily airplane congestion (on the surface of the airport) as an instrumental variable for pollution and focuses on children, adults, and the elderly. Their results confirm that pollution affects admissions for respiratory and heart-related diseases as wells as admissions for asthma. Specifically, an increase of one standard deviation in daily pollution increases hospitalization costs in $540.

Despite these health impacts, there is strong opposition to tightening ozone standards due to increasing marginal abatement costs (Cutter and Neidell, 2009). Reduced local governments' capacity often translates into high marginal costs of environmental quality improvements (Greenstone and Jack, 2015). High abatement costs paired with low marginal costs of self-protection can lead policymakers to prefer approaches that provide incentives to invest in self-protection rather than investing in better environmental quality. India and China have recently invested in developing robust pollution monitoring systems that help inform the population when they should take self-protection measures. In fact, today roughly 40% of the world's population lives a country that has air quality alert systems in its largest cities. Hence, governments sustain higher long-run pollution levels while using air quality warnings to avoid extremely hazardous days.

Some components of these policies have been studied before by economists. Barwick et al. (2019) find that after China launched a nationwide, real-time air quality monitoring and disclosure program, households' awareness about pollution increased. Access to real-time information on air quality caused adjustments in day-to-day consumption patterns to avoid pollution exposure and a higher willingness to pay for housing in less polluted areas, ultimately reducing the mortality impact of air pollution. In the US, many cities use air quality warnings without the mitigation component. These policies focus on encouraging people to reduce their emissions and avoid exposure. The results in the literature are mixed. For instance, in the case of air quality alerts in Sydney, estimates using administrative data indicate a reduction in cycling of 14% under OLS and 35% under IV (Saberian et al., 2017). In Salt Lake City, Tribby et al. (2013) find that alerts cause higher daily traffic at counters near the mountain canyons and decreases in the central city, suggesting that people "run away" to cleaner areas of the city. In contrast, Welch et al. (2005) find that the Ozone Action Days in Chicago do not significantly change subway ridership. All of these papers focus on the US and Europe. Developing countries, however, face additional challenges in implementation of environmental policies. In contexts of weaker institutional settings that hinder perfect compliance and are more prone to corruption, command and control policies face even more challenges. Oliva (2015) investigates the effect of bribing on vehicular smog checks in Mexico City. She finds that bribing occurs in more than 9.6% of tests, with the average bribe amounting to about $20 and that policies to reduce them are not cost-effective.

A growing strand of literature has studied avoidance behavior, which also underscores the importance of information. Avoidance behavior is sometimes intentionally driven by a policy, and sometimes it is a co-benefit (or offsetting mechanism) of information. Neidell (2009) shows that avoidance behavior taken in response to information on air quality generates downward biases to estimates of ozone's impact on asthma hospitalizations. With a regression discontinuity design, he first finds that people respond to warnings and do less outdoor activities. When incorporating those responses in estimates of the impact of ozone on asthma hospitalizations, the author shows that accounting for avoidance behavior yields estimates %40 larger than estimates that do not. Similarly, Moretti and Neidell (2011) use boat traffic as an instrument for ozone pollution. Since it is difficult for individuals to respond to ozone levels as affected by boat traffic, this approach holds compensatory behavior fixed. The massive difference from the OLS estimates underscores the importance of avoidance behavior in this context.

In all the examples above, avoidance behavior in response to information, while problematic for the empirical identification of the real magnitude of pollution's health effects, positively affects health. Information, however, can be a double-edged sword in environmental policy. Anticipation, facilitated by information, can undermine policy restrictions' effectiveness when people expect to be restricted in the future and are able to take preemptive measures to circumvent the restriction. Previous research has shown that anticipation changes both the timing and the overall effectiveness of environmental policies. This is the case for vehicle emission standards and marine conservation policy (McDermott et al., 2019; Rittenhouse and Zaragoza-Watkins, 2018). Based on their study of the Phoenix Islands Protected Area, McDermott et al. (2019) estimate that preemptive over-fishing in response to future restrictions could temporarily increase the share of over-extracted fisheries from 65% to 72%, which originates a "blue paradox." Similarly, Rittenhouse and Zaragoza-Watkins (2018) find that When agents expect a regulation to change the relative price of new equipment, they may shift purchases forward to avoid compliance costs, which under certain conditions, can completely turn the net environmental effect of the policy. In this paper, I find that information and mitigation do not undermine each other in the case of air quality warnings. On the contrary, when people anticipate that there will be driving restrictions on the next day, they start using their cars less since the moment that the future restrictions are announced. This reaction is potentially caused by higher awareness about the policy and pollution itself: google searches about pollution increase significantly when an alert is issued. These results highlight that health concerns can make people stay at home more and reduce their emissions. My results are more in line with Barwick et al. (2019), who highlight the power of information to reduce the health effects of pollution.

My findings contribute to the information and protective behavior literature and, more specifically, to the air quality warnings literature, which is focused on the US and Europe, has mostly overlooked programs that include mitigation, and has found mixed results on their effectiveness (See Neidell (2009); Welch et al. (2005); Saberian et al. (2017) and Tribby et al. (2013)). Temporary driving restrictions are part of air quality warning systems in several countries, but little is known about their effectiveness. We know that driving restrictions in Mexico and Colombia did not improve air quality in the long-run, and there are mixed results for China (Davis, 2008; Gallego et al., 2013; Zhang et al., 2017; Lin et al., 2011). However, these results do not say much about the value of driving restrictions as a short-run measure for protecting the general population from the impact of very polluted days, which is what China, India, and Mexico City aim at with their color-coded programs.

3 Background

3.1 The PCAA: measures and implementation

The Atmospheric Monitoring System (SIMAT) tracks the concentrations of air quality in Mexico City. When air pollution levels represent a risk to the health of the population, the Environmental Commission of the Megalopolis (CAMe) is informed so that they immediately enforce a series of measures to reduce pollutant emissions. This set of actions is called the Environmental and Atmospheric Contingency Program (PCAA for its Spanish acronym). Similar to its analogous programs worldwide, the PCAA includes both air pollution mitigation and adaptation measures, which are described in detail in Figure A.1. These measures are grouped in the following sectors: general population, businesses and services, authorities, transportation, and industry. The policy seeks to achieve very short-run reductions in outdoor air pollutants concentrations on its mitigation arm, mainly via restrictions on transport and industry. The adaptation arm acts through public health messaging that aims to inform the public about the risks of going outside and persuade them to reduce their exposure to pollution.

Until April 4th, 2016, the policy had three incremental phases; the threshold's evolution to declare each Phase is plotted in Figure 1. Pre-warnings focus on adaptation –communicating the current air quality and its associated health hazards and the precautionary measures that the population should take–, while Phases I and II add mitigation measures. Local mass media (newspapers, radio, television) and official media (*AIRE CMDX* app, official website, and social networks) are mandated by law to spread this information. Furthermore, once the alert (*contingencia*) is active, the CAMe performs a constant evaluation of meteorological conditions and updates the population at 10 am, 3 pm, and 8 pm through the channels mentioned above.

As shown in this figure, before 2016, the threshold to declare Phase I and Phase II was too high, so only pre-warnings were issued between 2005 and 2016. After the program was reformed on April 4th of that year, pre-warnings were eliminated, and the ozone threshold for Phase I was lowered to 155 ppb — the previous threshold for a pre-warning. This policy change creates a unique setting to examine whether an information policy is more effective when a mitigation component is added.

Mexico City has a longstanding license-plate based restrictions program, "*Hoy No Circula*", which independently of the PCAA, limits the circulation of 20% of the vehicles registered in the city year-round. The days in which cars can't circulate depend on their license plate, with two digits restricted each weekday. Using a car emissions verification system, [7] every vehicle registered in the city is assigned a category (00,0,1,2). Only cars within the 00 group are exempt from any restriction.

When Phase I of a PCAA alert is activated, the number of cars with a driving restriction is more than doubled from the regular "*Hoy No Circula*." 20% of vehicles on the 00 category, plus an additional 40% of cars in category 0 and 1, and 100% of vehicles in category 2 must stay off the streets. [8] Davis (2008) finds that the regular *Hoy No Circula* has no effect on traffic and worsens pollution, but the PCAA restrictions differ from regular HNC program in two important ways. First, the selection of cars randomly changes with each alert. Second, these restrictions are only announced the day before they are enacted. In contrast, HNC restrictions never vary, so if a car has a restriction on Tuesdays, this will always be the case, making it easier to anticipate this restriction. Given these two differences, the effect of these additional restrictions is not clear *a-priori*.

The PCAA also mandates that firms and factories cut back their emissions by 40% during Phase I and by 60% during Phase II. Since 2019, the public-owned industrial complex that includes a refinery and a thermoelectric plant located 40 kilometers away from Mexico City lower their production by 25% (or 45% in Phase II) and 30%, respectively.

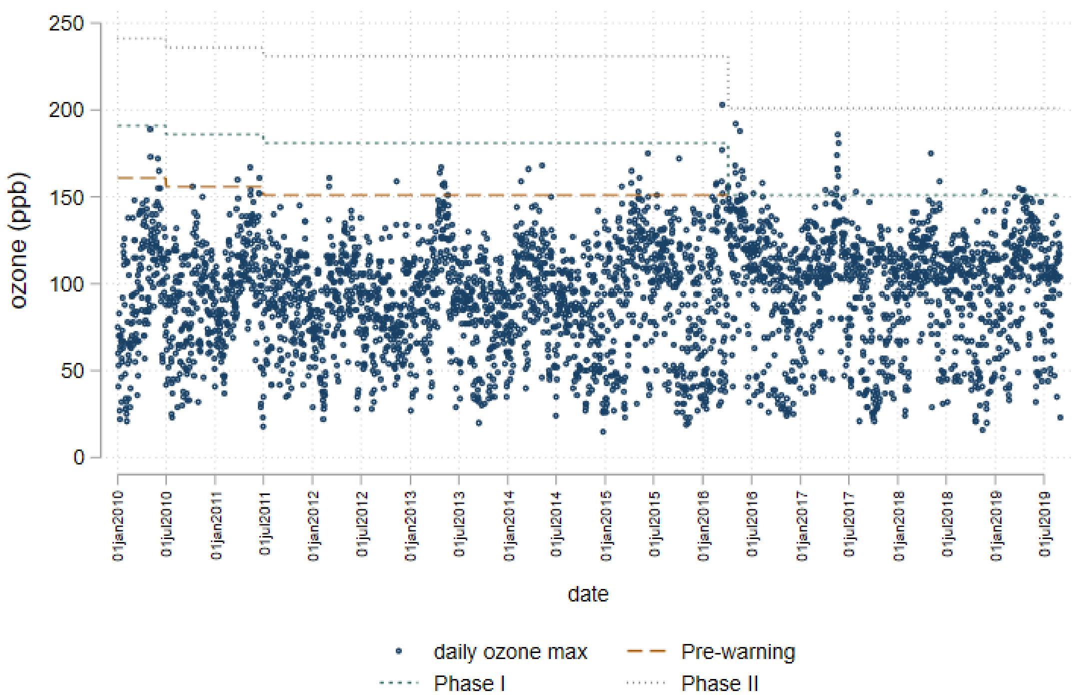
3.2 Typical progress of an alert

PCAA alerts are usually issued in the afternoon, when ozone reaches its maximum concentrations. The mode of the activation hour is 4 pm (32%), followed by 3 pm (24%) and 5 pm (24%). Once the alert is active, a monitoring committee is in charge of determining when pollution and weather conditions allow to deactivate the alert. Most of the alerts last around 24-27 hours (41%). Figure A.2 in the Appendix shows in detail the distribution of the duration of the alerts. An important feature is that an alert is activated when

[7] See Oliva (2015) for more information about the smog check program.

[8] On Phase II, 50% of motorcycles must stop circulating. Additionally, government vehicles are not allowed to transit. However, the threshold for Phase II is two high, and in practice, none of these measures are implemented.

Figure 1: **PCAA thresholds and Maximum daily ozone readings**



Note: Figure shows the evolution of the thresholds for each Phase of the program since 2010. The dots represent a 5% sample of the maximum daily monitor-level ozone readings, measured in parts per billion. Threshold data was built using official communications published in the Mexico City Gazettes. This figure highlights how before 2016, the threshold to declare Phase I and Phase II was too high, so only pre-warnings were issued between 2005 and 2016. After the program was reformed on April 4th of that year, the pre-warnings were eliminated, and the threshold for Phase I was lowered to 155 ppb of Ozone, which was the previous threshold for a pre-warning.

any monitoring station surpasses the ozone concentrations threshold. Figure 2 shows the evolution of each pollutant before and after an alert. An alert is usually preceded by an anomaly in pollution that drives levels slightly above the threshold and followed by mean reversion driven by hourly patterns in meteorological conditions and human activity. The threshold is quite high; hence ozone levels never stay above it for long, and since ozone alerts are issued in the afternoons, most other pollutants will have decreased by then.[9]

When the alert is announced, it is usually around 4pm. The government broadcasts health information and announces the measures to be taken. The driving restrictions enter into place until the next morning at 5am, as shown in Figure 3, which focuses on the alert issued on 08-07-2016. This particular alert lasted for 24 hours, so it was desactivated at 4pm of 08-08-2016 –the recond red line in Figure 3.

4 Data

I use four data sources to estimate my four main sets of results: hospital-level health outcomes, monitor level pollution and weather data, sensor-level traffic data, and awareness data from Google trends. In this section, I describe these data sources and present some descriptive analysis of the data.

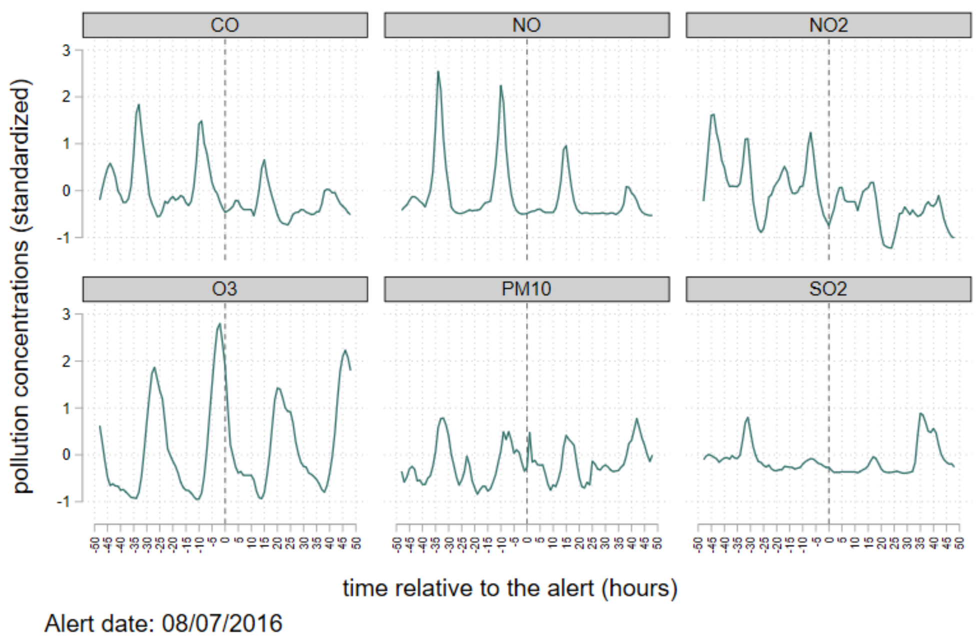
I use monitor-level data from the Atmospheric Monitoring System (SIMAT), covering January 2016-August, 2019, in Mexico City. This agency publishes hourly average concentrations of several pollutants, including PM10, Ozone, NOX, CO, SO2, NO2, and hourly average weather conditions, including wind speed and direction, relative humidity, and temperature. From the SIMAT website, I also obtained the historical account of all the alerts issued since 1996 and a detailed list of all the program's modifications since then.

Table 1, shows that transport accounts for more than 80% of CO emissions and more than 70% of NOX (NO and NO2). On the other hand, urban waste, agriculture, vegetation, and road construction drive the bulk of PM10 emissions, leaving only 12% for personal cars, 22% for other vehicles. Most of the SO2 comes from combustion, especially from industries near the city, such as the Tula refinery-power plant.

Figure 4 shows the geographical distribution of pollution monitors, along with the lo-

[9]This also shown, including a larger sample of alerts, in Figure A.3 in the Appendix.

Figure 2: Typical progress of an air quality warning



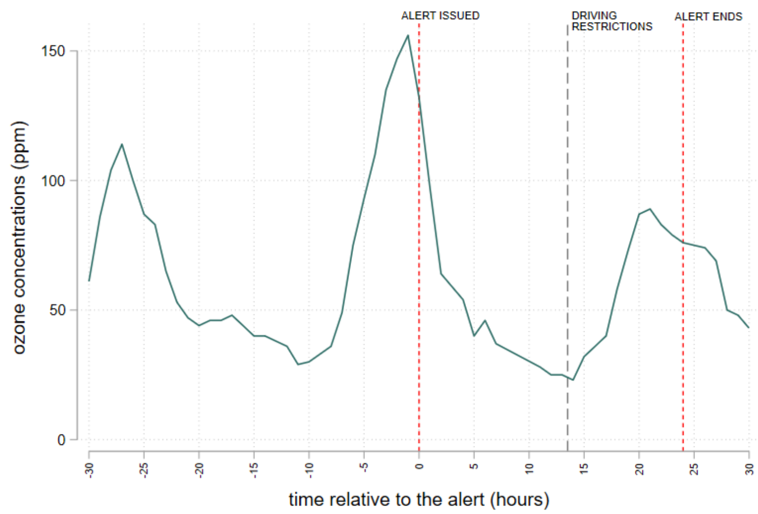
Note: Figure compares the trajectory of carbon monoxide (CO), nitrate oxides (NO and NO2), ozone (O3), particulate matter (PM10) and sulphur dioxide (SO2) on the 48 hours before and after a PCAA alert. Each line represents the hourly average of monitor-level readings, standardized. Historical time series of alerts was built using official communications published in the Mexico City Gazettes.

Table 1: **Emissions in Mexico City by particle and type of source.**

	Total	**Industry**	**Area sources**	**Mobile sources**	**Others**
Particle			Emissions [ton/year]		
PM10	35,274.0	3,574.3	20,015.3	10,899.1	785.3
PM2.5	14,012.0	2,526.3	5,876.1	5,437.8	172.1
SO2	2,466.0	1,150.8	980.7	334.0	0.0
CO	643,921.0	6,277.7	23,811.9	613,831.7	0.0
NOX	140,156.0	11,915.0	14,264.1	112,350.0	1,627.2
		Industry	**Area sources**	**Mobile sources**	**Others**
Particle			Percentage		
PM10		10.1%	56.7%	30.9%	2.2%
PM2.5		18.0%	41.9%	38.8%	1.2%
SO2		46.7%	39.8%	13.5%	0.0%
CO		1.0%	3.7%	95.3%	0.0%
NOX		8.5%	10.2%	80.2%	1.2%

Note: Percentages calculated using the Mexico City Emissions Inventory, 2016. This document, prepared by the Secretariat of the Environment, brings together the report of emissions of criteria pollutants, toxic, gases and greenhouse effect compounds of 93 categories: 25 point sources, 55 categories of area sources, 11 types of vehicles and two natural sources. For the development of this Inventory, methodologies described in the Manuals of the Emissions Inventory Program of Mexico, the California Environmental Protection Agency, the United States Environmental Protection Agency and the Intergovernmental Panel on Climate Change were used. (CalEPA, US-EPA and IPCC). Ozone is not included in emissions inventories because it not directly emitted by any source, but is formed when oxides of nitrogen (NOx) and volatile organic compounds (VOCs) react in the presence of sunlight.

Figure 3: Timing of restrictions: example from alert issued on August 7th, 2016



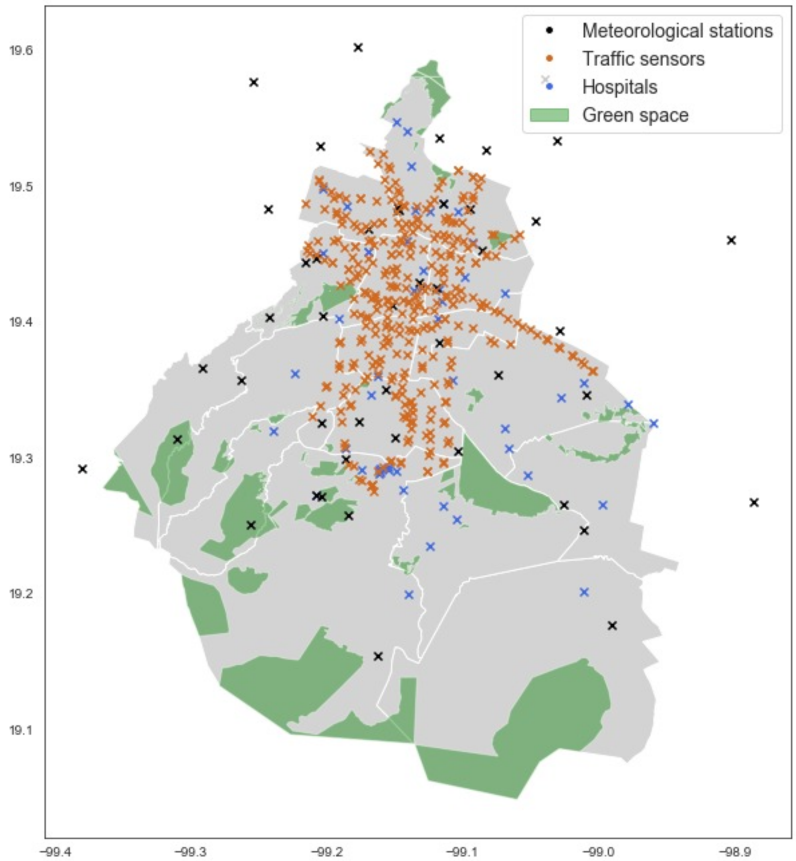
Note: Figure shows the trajectory of ozone (O3) on the 48 hours before and after the PCAA alert issued on August 7th, 2016. The line represents the hourly average of monitor-level readings.

cation of the hospitals matched to them, and the traffic sensors used for the congestion analysis.

To look at the health impacts of PCAA alerts, I use data on ER visits for cardiovascular disease, respiratory diseases, and asthma, obtained from public hospital administrative records. These records are publicly available and include all the hospitals within the Ministry of Health (Secretaría de Salud) system and some independent national hospitals. While this sample lacks data from private hospitals, it does cover the bulk of the public health system. Only 7% of the population has private insurance nationwide, although there is considerable regional variation (Juan Lopez et al., 2015).

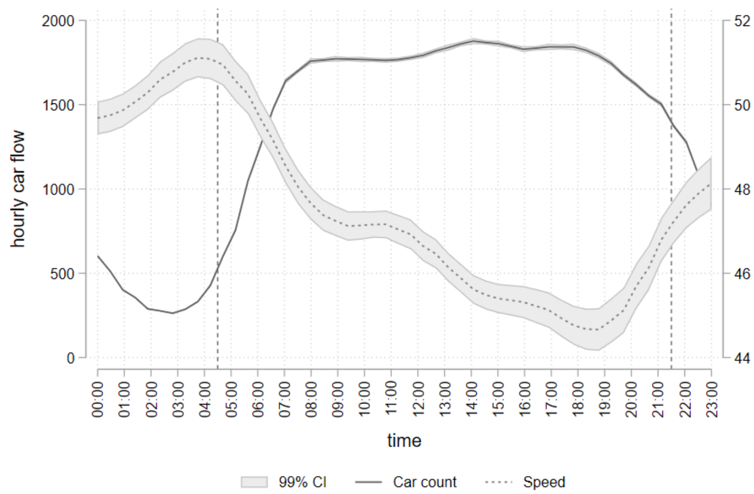
From Mexico City Open Data Portal, I obtained hourly traffic data from 343 sensors and video detectors located throughout the city. This data set contains 10.3 million observations of hourly car counts by vehicle type and average car speed between 2016 and 2017. Figure 5 shows the hourly average car count and speed as measured by the sensors and video detectors. Since average speed has *a priori* a monotonic relationship with the actual number of cars in the street, due to the effect of congestion and bottlenecks on car counts, speed

Figure 4: **Data -** Sources and Coverage



Note: The location of the collection points for the main variables in the paper are included in this map. This includes a) weather monitoring stations that also collect pollution data, b) traffic monitors (sensors and video) and c) all the public hospitals in Mexico city. Areas covered by vegetation are highlighted in green will be my preferred measure of car usage.

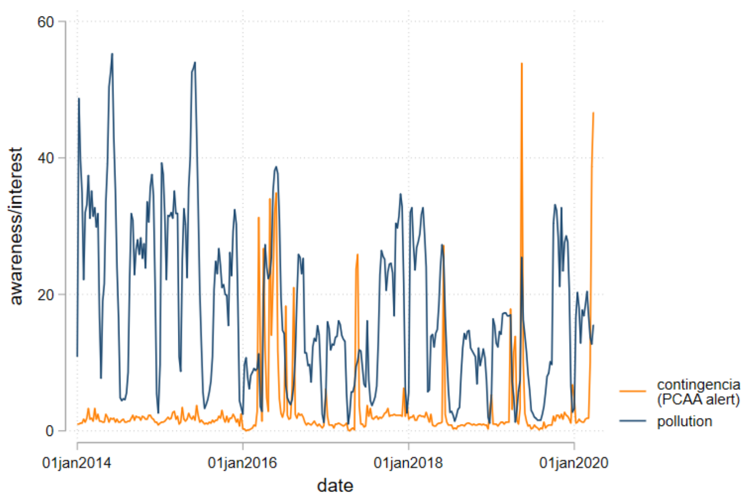
Figure 5: **Traffic data**



Note: Figure displays usual hourly speed and flow averages. Local polynomial and 90% confidence intervals are included. Observations are collected from 343 monitors and video detectors in the city, in points highlighted in Figure 4. Speed is measured in km/h and flow in cars counted per hour. Data was obtained from the CDMX Open Data Portal

To analyze the impact of the 2016 reform on the policy's salience, I create an awareness measure using search indexes from Google Trends. To construct each search index, search results are normalized to the time and location of a query. Each data point is divided by the total searches of the geography and time range it represents to compare relative popularity. The resulting numbers are then scaled on a range of 0 to 100 based on a topic's proportion to searches on all topics. Figure 6 shows the evolution of interest over time on pollution and the PCAA alerts. Interest in pollution has decreased over time, along with the slow but steady improvements in air quality that the city has experienced. On the other hand, interest in the PCAA program, which has existed since the 1990's, was practically zero until 2016. In section 8.2, I show the short-run impact of alerts on awareness about air pollution in general, and the PCAA.

Figure 6: **Interest over time: pollution and PCAA alerts**



Note: Figure shows the search index in Google Trends for the word *contingencia*(the name of the alert in Spanish) and for the word *contaminación* (pollution). Data includes daily search indexes from 2013 to 2019, for the entire country. Search results are normalized to the time and location of a query.

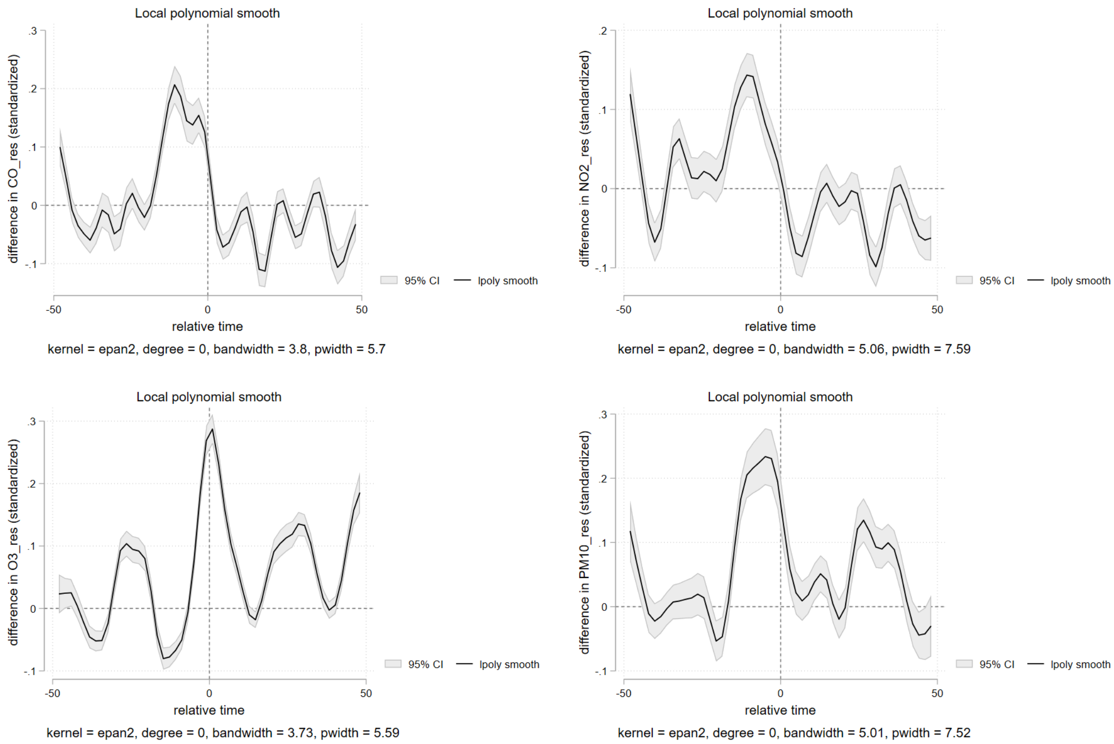
5 Empirical strategy

An alert is declared whenever ozone levels surpass 155 ppb in any station in the city. This threshold has been made progressively stricter through time as overall air quality in Mexico City improves, as shown in Figure 1. A visual continuity test, shown in Figure A.4 rules out bunching around the threshold for the activation of the alert. This setting allows me to compare alert days with similar trajectories but that barely missed the threshold and identify the causal impact of a warning being issued.[10]

However, the threshold to declare a PCAA alert —150ppb of ozone— is very high compared to its distribution. Between 2016 and 2019, this threshold was exceeded only 0.31% of the time, and only 16 alerts were issued. Figure 7 shows the evolution of pollution when comparing the 24 hours before and after the alert with a control 48 hours time series,

[10]The setup mentioned above suggests an opportunity for using a regression discontinuity design to find the causal impact of air quality alerts on health. However, as described in Section 4, the program has two features that undermine this strategy: a) alerts are declared based on the current hourly concentration of ozone instead of a forecast, and b) the threshold is set at the top of the hourly distribution of pollution. Also, pollution is not expected to change discontinuously at the exact moment of the alert.

Figure 7: **Difference in air pollution (alert-previous week)**



obtained averaging seven days before and seven days after the warning, in a similar spirit to Anderson (2014). As shown in this Figure, an alert happens on an exceptionally polluted day. It is preceded by an anomaly in pollution that is not similar to the trajectory observed on that day the week before and after, even when controlling for seasonal variation using a saturated set of fixed effects. An ideal counterfactual also has an anomaly in pollution that is not followed by an alert. I generate this counterfactual using the synthetic control method proposed by Abadie et al. (2010, 2015), which is a commonly used approach for case studies. Importantly, this approach also allows me to account for potential mean reversion, which could be driving some of the substantial reductions that we observe in Figure 7 after an alert is issued.

5.1 Effect of alerts on pollution

To estimate the effect of each alert on pollution, I use the synthetic control method. This strategy aims to match each alert day to a weighted average of potential controls. The method seeks to minimize the difference on expected pollution, driven by meteorological conditions and past pollution levels, between the treated day and its counterfactual. For each day $j \in J$ in the sample, let $Y_j = (Y_{j,-c}, ..., Y_{j,0}, ..., Y_{j,C})'$ be the observed outcome vector of $C + c$ hours. Let $K \subset J$ be the set of 16 ozone-driven air quality alerts between April 2016 and May 2019. To each alert, I associate a buffer of $t \in [-c, C]$ hours, indexed in relation to the activation of the alert, which is set as $t = 0$. [11] The observed outcome vector of each alert $k \in K$ is $Y_k = (Y_{k,-c}, ..., Y_{k,0}, ..., Y_{k,C})'$.

Following Abadie et al. (2010), the observed outcome at every period can be written as the sum of a treatment-free potential outcome, Y_{jt}^N, and the effect of the treatment, α_{jt}, such that

$$Y_{jt} = Y_{jt}^N + \alpha_{jt} D_{jt} \tag{1}$$

$$Y_{jt}^N = \delta_t + \theta_t Z_j + \lambda_t \mu_j + \varepsilon_{jt} \tag{2}$$

Where $D_{jt} = 1 \forall k \in K$ if $t \geq 0$ δ_t is an unknown time fixed effect, Z_j is a vector of observed meteorological covariates unaffected by treatment with time-varying coefficient vector θ_t, μ_j is a vector of time-invariant unobserved predictor variables with time-varying coefficients λ_t and the error ε_{jt} is independent across units and time with zero mean.

The synthetic control method generalizes the difference-in-differences method by allowing the effects $lambda_t$ of the unobserved predictors μ_j to vary over time, while the DiD method constrains these effects to be constant. The assumption is that this flexibility is achieved by controlling for the trajectory of the dependent variable. In the case of this study, I create a synthetic day that exhibits similar pre-warning anomalies in pollution as the treated day.

For periods after $t = 0$, Y_{kt}^N, is not observed. To estimate the treatment effect for the post-intervention periods, the synthetic control method estimates the unobserved Y_{kt}^N

[11] Note that C and c may both be >24, which means that a single calendar day may enter several sets, exploiting the variation in the relative position of that hour with respect to 4 pm hour of every calendar date.

by creating a "synthetic control unit": a weighted average of potential controls that best approximates the relevant pre-alert characteristics of the treated day. Let $m = 1, ..., M$, with $M = J - K$ be the set of control days, and $W_k = (w_{k1}, ..., w_{kM})'$, where w_{km} is the contribution of each day in to the synthetic control unit. The counterfactual for each alert Y_k is constructed as the linear combination of the observed outcomes of the potential control days: $\hat{Y_{kt}^N} = \sum_{m=1}^{M} w_{km} Y_{mt}$. The estimated treatment effect for each alert for each time period after $t = 0$ is $\hat{\alpha_{jt}} = Y_{kt} - \hat{Y_{kt}^N}$.

The vector W_k^* is chosen to minimize the difference in observed and unobserved confounders before the activation of the warning, between each treated day and its synthetic control. This difference is measured with the following distance metric:

$$\sqrt{(X_k - X_k W_k)' V (X_k - X_0 W_k)}$$

where X_k is a p×1 vector including p covariates and pre-treatment outcomes for the treated day k. X_0 is the corresponding p×M matrix of the control days. V is a p×p positive definite and diagonal matrix, which assigns weights according to the covariates' relative importance and the seasonally-adjusted pre-intervention outcomes. The covariates used to define a synthetic day are only the seasonally-adjusted meteorological conditions: wind speed, temperature, and precipitation. To obtain the results on overall citywide pollution levels, I created an air pollution index (API), which is the first component obtained from a principal component analysis of NO2, CO, PM10, PM25, O3, and SO2. This index is my preferred dependent variable.

To calculate the statistical significance of the estimated treatment effects, I run placebo tests by assigning treatment status and applying the synthetic control method to each control unit, following Abadie et al. (2010) and Galiani and Quistorff (2017). The significance is calculated by comparing the estimated treatment effect to the distribution of placebo effects:

$$p - value_{\alpha_t} = \frac{\sum_{m=1}^{M} |\mathbb{1}(\hat{\alpha_{mt}} \geq \hat{\alpha}_t)|}{M} \tag{3}$$

5.2 Effect of alerts on health

This paper also estimates the health effects of the PCAA alerts. These effects are expected to happen on two margins: a) on the mitigation margin, the policy is reducing the levels of pollutants in the air, which is expected to generate health benefits, and b) on the adaptation margin, the PCAA program seeks to incentivize people to take protective measures such as staying at home. In this section, I describe the instrumental variable strategy that I use to measure the net effect of the policy on health.

The rationale for the synthetic controls was to emulate intra-day patterns of pollution and control for mean reversion after the daily maximum. However, for health outcomes, intra-day patterns seem to reflect mostly the shift structure of the hospital, with peaks every 8 hours and nothing much happening the rest of the day. Hence, controlling for preivous intra-day trajectories of ER visits does not make much sense in this case.

Hence, I expand on the strategy followed by Deryugina et al. (2019), who instrument for daily changes in a county's daily average PM 2.5 concentrations using changes in the county's daily average wind direction. The mechanisms mediating the impact of wind direction and speed on pollution are a) redistribution of locally produced pollution (e.g., traffic or local power plants) and b) transport of externally produced pollution into the city. In Mexico City, SO2 emissions are mostly driven by transported particles. The public-owned industrial complex that includes a refinery and a thermoelectric plant located 40 km away from the outer edge of the Metropolitan Area in Tula, Hidalgo, emit 33 times more SO2 and PM2.5 than the whole of Mexico City and conurbation. It is the single most polluting plant in Mexico and the second most polluting in North America (CCAC, 2020). With this external source of pollution accounting for such a sweeping fraction of concentrations for some pollutants, wind speed and direction, responsible for these particles' transport, are significant predictors of pollution in Mexico City. This does not mean that car emissions inside the city - and how fast these emissions are dispersed by wind- are not an important source of pollution. As shown in Table 1, both the industry (including the Tula plant) and mobile sources drive pollution levels in the city.

In this paper, I use wind speed and direction as a source of external variation in air pollution. This strategy aims to obtain a predicted pollution control to quantify the health effects of policy-induced reductions in air pollution. The rationale behind this strategy is to compare PCAA days with days with similar weather-driven pollution. The assumption is that by controlling for predicted pollution, then the effects of mitigation (deviations from predicted pollution) and adaptation (protective measures when notified that air quality can be hazardous) are captured by the relative change in health outcomes after the alert's activation, once controlling for weather-driven pollution. The first stage equation is the following:

$$API_{i,j} = \Phi_{ij} wsp_{ij} + f(wdr_{ij}) + \Theta_j + Xij + \varepsilon_{ij} \tag{4}$$

In Equation 4, the air pollution index on day j in hospital i, is a function of wind speed wsp_{ij} and direction wdr_{ij}. $f(wdr)$ is a flexible function of wind direction that contains a series of 10-degree dummies. Θ_j is a vector of time fixed effects and their interactions (day-of-the-year, month, hour,day-of-the-week, year), X_{ij} is a set of weather controls and their interactions, and ε_{ij} are the Newey-West standard errors robust to autocorrelation in four lags. The results of this specification are presented in Section 7. Table 2 shows the first stage results. Column (1) includes only the wind speed instruments, capturing the average, maximum, and minimum windspeed in the city at that hour. Column (2) includes ten bins of 36° for clarity (a table with the full set of 10° indicators is presented in the Appendix. in Table A.2), and Column (3) includes both. A visual representation of the impact of wind direction on each pollutant's monitor-level readings is presented in Figure A.6 and Figure A.7 in Appendix.

This strategy aims to obtain a predicted pollution control to quantify the health effects arising from policy-induced reductions in air pollution. Since pollution is endogenous to the intervention, an exogenous pollution control is necessary to parse out the net effect of the policy. This strategy is not instrumenting the treatment, it is instrumenting the pollution control using wind speed and direction. The second stage is constructed as follows:

$$Y_{ij} = \sum_{t=-5}^{5} \alpha_j \mathbb{1}[j - j_{start} = t] + \sum_{q=0}^{4} \gamma_q API_{p,j-q} + \theta_j + Xij + \epsilon_{ij} \tag{5}$$

The ER admissions for hospital i in day j are a function of an event-study type set of time dummies relative to the alert activation. θ_j is a matrix of time fixed effects and their

Table 2: Impact of wind direction and wind speed on pollution

VARIABLES	(1) API	(2) API	(3) API
$0^\circ < wdr_{it} < 36^\circ$		-1.516***	1.686***
		(0.0643)	(0.0459)
$36^\circ < wdr_{it} < 72^\circ$		-0.910***	1.479***
		(0.0566)	(0.0155)
$72^\circ < wdr_{it} < 108^\circ$		0.192***	1.706***
		(0.0559)	(0.0124)
$108^\circ < wdr_{it} < 144^\circ$		0.377***	1.643***
		(0.0552)	(0.0103)
$144^\circ < wdr_{it} < 180^\circ$		0.278***	1.512***
		(0.0548)	(0.00916)
$180^\circ < wdr_{it} < 216^\circ$		0.0205	1.291***
		(0.0548)	(0.00855)
$216^\circ < wdr_{it} < 252^\circ$		-0.286***	1.068***
		(0.0551)	(0.00878)
$252^\circ < wdr_{it} < 288^\circ$		-0.534***	0.979***
		(0.0551)	(0.00962)
$288^\circ < wdr_{it} < 324^\circ$		-0.813***	0.863***
		(0.0557)	(0.0148)
$324^\circ < wdr_{it} < 360^\circ$		-1.585***	0.121**
		(0.0688)	(0.0615)
WSP_{mean}	-0.302***		-0.828***
	(0.00718)		(0.00769)
WSP_{min}	-0.203***		0.157***
	(0.00627)		(0.00602)
WSP_{max}	0.101***		0.00522*
	(0.00323)		(0.00308)
Observations	867,878	867,878	867,878
F-Stat	14610	2120	9810
Prob > F	0	0	0
Degree of Freedom	867875	867867	867865

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: The table shows the correlation between wind speed, wind direction and pollution concentrations. The dependent variable is the Air Pollution Index (API), obtained from a principal component analysis, as described in Section 9. 36-degree bins are used to measure wind direction flexibly. The sample is restricted to January 2016 to December 2019. Pollution and weather data were obtained from monitor-level hourly readings.

interactions (day-of-the-year, month, hour,day-of-the-week, year), X_{ij} is a set of weather controls and their interactions, and ϵ_{ij} are the Newey-West standard errors robust to autocorrelation in four lags. Four lags of the weather-driven pollution $API_{i,j}$ are included. The parameters of interest are the coefficients of the event study dummies, α_j. For this specification, I assume that people go to the hospital closest to their location on that day, which is a reasonable assumption given that these are ER visits. The hospital-level conditions are estimated using the readings from the three closest meteorological monitoring stations. The results of this specification are presented in Section 7.

6 Impacts of Air Quality Warnings on Pollution

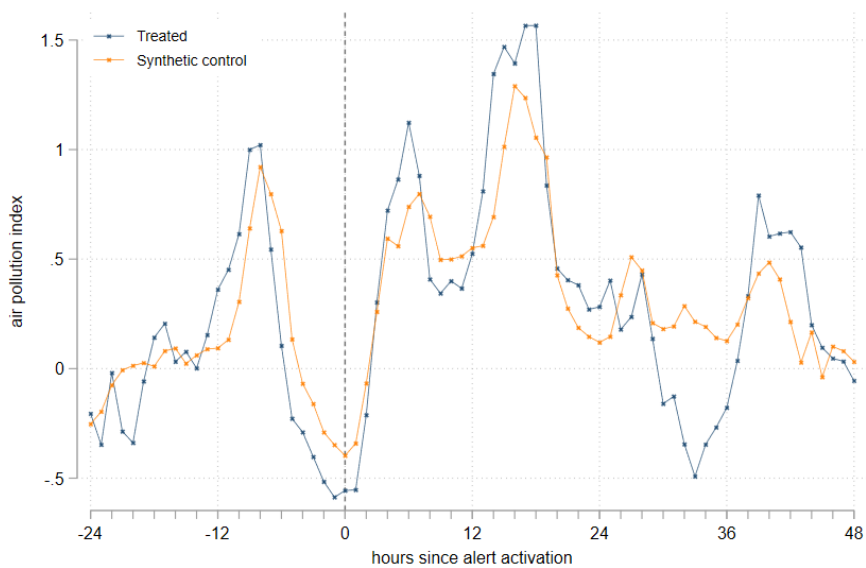
This section presents the impact of PCAA alerts on hourly air pollution levels before and after the policy change on April 4th, 2016. I find that before 2016, there is no difference between alert days and the counterfactual. However, after 2016, there are significant pollution reductions during the first day of the alert, driven mostly by decreases in NO2 and CO emissions.

6.1 Pre-reform

As described in Section 3.2, during this time, only pre-warnings –which advise the population about hazardous air pollution and extend a series of recommendations– were issued. The overall effects of the people's protective measures in response to an alert on air quality could go in either direction. Some people may try to stay at home and reduce their emissions. However, other protective measures, such as using the car instead of more exposure-intensive modes of transportation, could revert these effects.

Figure 8 shows, in blue, the average trajectory of pollution around the start of a PCAA alert during the pre-reform period, in which the program only included a pre-warning (precontingencia) whenever ozone surpassed 155 ppb. The threshold for mitigation measures was too high and was never reached during this period. There is no statistically significant difference between the Y_jt and its counterfactual $\widehat{Y_{jt}^N}$, which is show in orange and was constructed using the synthetic control methods. These results imply that, before the reform, the policy did not have any impact on air pollution. The lack of effects on pollution is not surprising: there were no mandatory mitigation measures included in the alerts issued

Figure 8: **Impacts of PCAA on air pollution, pre-reform**



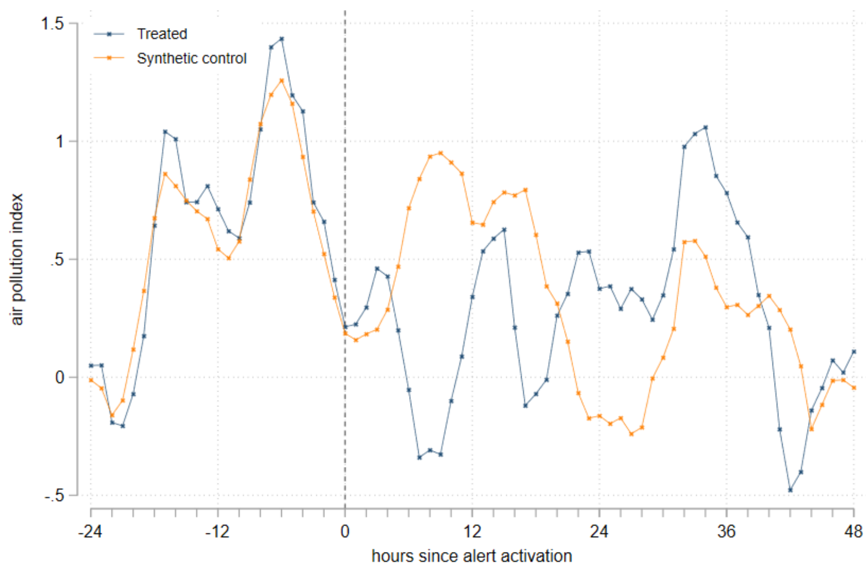
Note: Figure shows the trajectory of air pollution before and after the activation of an alert, denoted by Y_{kt}. The counterfactual $\hat{Y}_{kt}^{N}$ is estimated using a weighted average of other days in the sample. The covariates used to select from the donor pool are: AQI, wind speed, temperature, and relative humidity. The period used for this selection is the 24 hours previous to the activation of the alert. The sample is restricted to January 2013 to April 4th, 2016. Pollution data was obtained from monitor-level hourly readings. The Air Pollution Index (API) is constructed using the first component obtained from a principal components analysis of standardized NO2, CO, PM10, PM25, O3, and SO.

before 2016.

6.2 Post-reform

Figure 9 shows the trajectory of pollution before and after the start of the average PCAA alert and its counterfactual. The sample is now restricted to alerts that happened during the post-reform period. This figure, along with Figure 8, helps underscore the relevance of the synthetic control method for this particular setting. By the time the alert is issued, most contaminants - and consequently, the API- are already on a downward trajectory. This pattern is due to the typical hourly variation in pollution for most particles. Hence, I need to use a method that accounts for mean reversion and explicitly shows differences in hourly pollution patterns.

Figure 9: **Impacts of PCAA on air pollution: treated and control days, post-reform**



Note: Figure shows the trajectory of air pollution before and after the activation of an alert, denoted by Y_{kt}. The counterfactual $\hat{Y_{kt}^N}$ is estimated using a weighted average of other days in the sample. The covariates used to select from the donor pool are: AQI, wind speed, temperature, and relative humidity. The period used for this selection is the 24 hours previous to the activation of the alert. The sample covers from April 4th, 2016, to December 31st, 2019. Pollution data was obtained from monitor-level hourly readings. The Air Pollution Index (API) is constructed using the first component obtained from a principal components analysis of standardized NO2, CO, PM10, PM25, O3, and SO.

The visual evidence in Figure 9 allow us to rule out mean reversion as a driver of the results. Creating a synthetic day that has followed this particular trajectory, I account for within and between/days mean reversion. The difference between Figures 8 and 9, shed light on the effect of the post-2016 restrictions on pollution. An alert lasts, on average, approximately 24 hours. There is an overall reduction in pollution and a displacement towards the second day after the alert is issued.

Figure 10 shows the $\widehat{\alpha_{jt}}$, this is, the difference between the treated day and its counterfactual, measured as the reductions in the API during alerts issued after the 2016 policy change. The policy introduced a series of driving and production restrictions listed in Figure A.1, which would catalyze strong reductions in pollution if successful. The cumulative reductions in the API in the first 24 hours, represented by the area under the curve, amount to 7.17 times the hourly average. While there are some increases at some specific hours of the second day of the alert, by calculating the area under the curve of $\widehat{\alpha_{jt}}$, I find a cumulative reduction in exposure of 2.5 standard deviations.

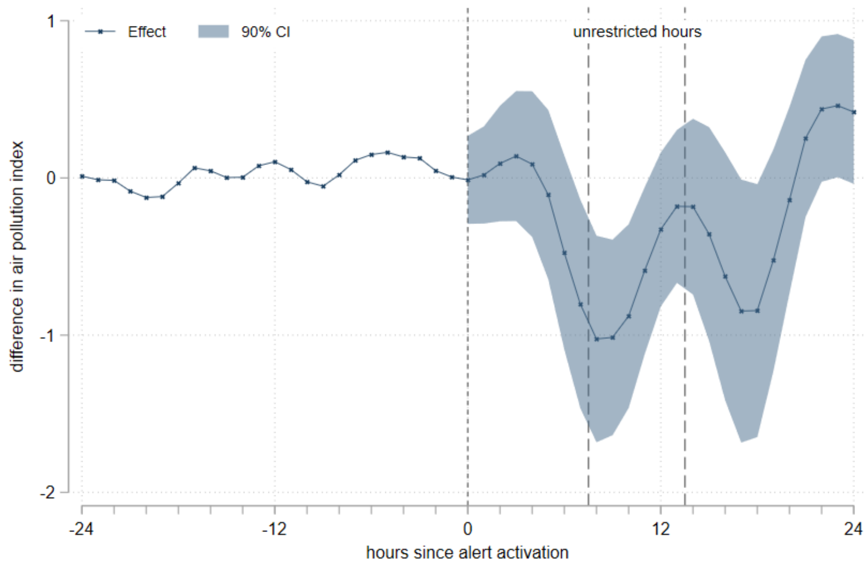
The license-plate based driving restrictions enacted in PCAA only operate between 5 am and 10 pm, leaving some scope for within-day shifts in travel time. As shown in Figure 10, pollution also follows a within-day pattern that matches the within-day changes in restrictions. Unrestricted hours occur on average between hour 7 and 14 after the activation of the alert. In the plot, these hours are highlighted in dotted lines. The rebound in air pollution concentrations during unrestricted hours is so strong that the effect is almost entirely reverted. In section 8, I show that nocturnal increases in pollution are driven by significant switching in travel times: if restrictions operate between 5am and 10pm, then a proportion of the people who have necessary trips on alert days switch towards unrestricted hours (11pm-4am).

Figure 11 shows the impact of the activation of an alert on each pollutant. This figure highlights that reductions in NO2 and CO drive the aggregate pollution results. These findings are consistent with the distribution of emission sources per pollutant described in Figure A.3, since transport accounts for more than 80% of CO emissions and more than 70% of NOX. Furthermore, the amount of carbon monoxide and nitrous oxide emissions is an order of magnitude above those of particulate matter or SO2, which leaves more scope for reduction in the former.

On the other hand, urban waste, agriculture, vegetation, and road construction drive the bulk of PM10 emissions, leaving only 12% for personal cars, 22% for other vehicles. Most SO2 emissions come from combustion, especially from industries near the city, such as the Tula refinery-power plant. SO2 remains mostly unaffected, and PM10 presents an increase during the first few hours of the alert. While in paper, there are some industry restrictions, the lack of effect on SO2 reflects the absence of changes in combustion practices. [12] These results provide significant policy insights because they highlight which regulations are better

[12]Since 2019, when Phase I of PCAA is activated, the Tula refinery and the thermoelectric must lower their production by 25% and 30%, respectively. Data on alerts after this change is not available yet. However, it is plausible that the results on SO2 will change for alerts that included shutdowns on these vast emitters.

Figure 10: **Impacts of PCAA on air pollution, post-reform**



enforced and more successful in reducing pollution. Driving restrictions may be costly to implement, but they are successful in reducing automobile emissions. The law includes audits to firms, intending to find non-compliers. The consequences of non-complying include fines and closures. However, the policy's failure to reduce industry-driven emissions suggests that the current mechanisms are not enough to enforce widespread compliance.

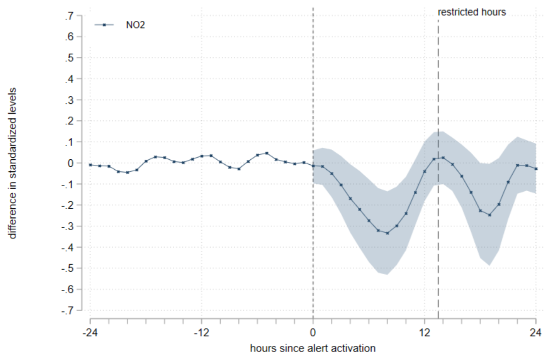
7 Effects on Health

In this section, I present the impacts of air quality warnings on ER visits before and after the reform in 2016. To estimate these impacts, I match each hospital to the three closest meteorological stations, capturing hourly weather conditions and pollution levels. I assume that people go to the hospital that is closest to their location on that day. If this premise is correct, then hospital-level pollution captures well the pollution to which they were exposed. This assumption is reasonable since I use unplanned ER visits.

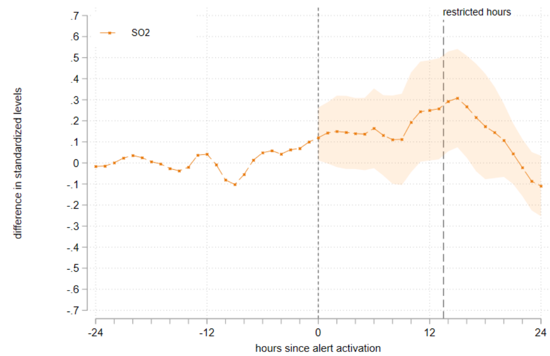
I show that these effects are absent before 2016, but they are substantial and last several days after post-reform alerts. This difference implies that the driving force behind the

Figure 11: **Effect of PCAA activation on pollution - by particle**

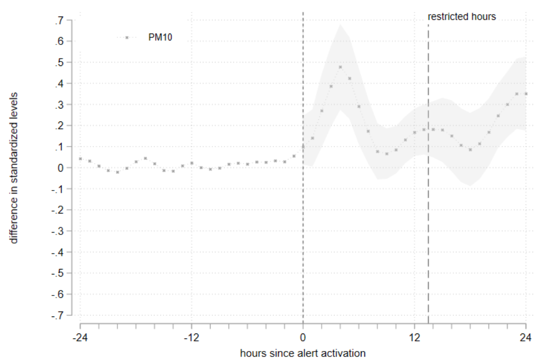
(a) NO2



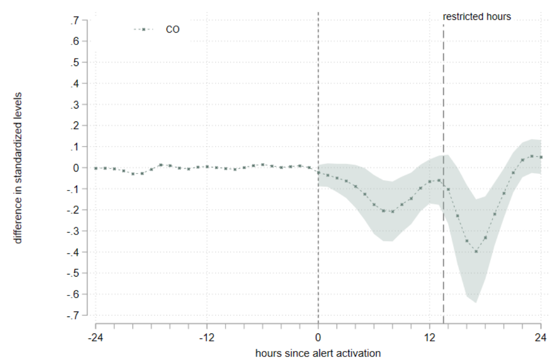
(b) SO2



(c) PM10



(d) CO



Note: Figure shows the trajectory of air pollution before and after the activation of an alert, denoted by Y_{kt}. The counterfactual $\hat{Y_{kt}^{N}}$ is estimated using a weighted average of other days in the sample. The covariates used to select from the donor pool are: pollution concentrations of SO2, NO2, PM10 and CO for panels a), b), c) and d), respectively, wind speed, temperature, and relative humidity. The period used for this selection is the 24 hours previous to the activation of the alert. The sample covers from April 4th, 2016, to December 31st, 2019. Pollution data was obtained from monitor-level hourly readings. The Air Pollution Index (API) is constructed using the first component obtained from a principal components analysis of standardized NO2, CO, PM10, PM25, O3, and SO.

observed health benefits is the mitigation from reduced emissions. In section 8, I show that there is evidence of some adaptation occurring after 2016: despite the driving restrictions, there are also fewer people using public transportation in PCAA days.

7.1 Pre-reform

As disussed in Section 6, pre-2016 alerts had no impact on pollution. However, there could still be a decrease in acute morbidity if people adapt to high levels of pollution by following the health advice communicated by the authorities and take protective measures against pollution. Previous research has found that public health messaging that informs the population about hazardous air pollution can incentivize protective behavior in some contexts. These protective measures can reduce the health impacts of pollution (Neidell, 2009). In this paper, I show that in the absence of mitigation measures, this was not the case for Mexico City before 2016.

Table 3 shows the impacts of an alert issued before the reform on ER visits for cardiovascular and respiratory diseases, using the econometric specification described in Section 5.2. This identification controls for predicted pollution using wind speed and direction as sources of external variation. After the alert is issued, there is a marginally statistically significant 0.013 standard deviation increase in general ER respiratory visits and a 0.005 non-significant standard deviation increase in children and elderly admissions. There is no statistically significant change in other health outcomes, except for a large but marginally significant decrease in asthma admissions of vulnerable populations on the day the alert is issued. The increases in ER visits of respiratory diseases last for three days.

The policy was mostly unsuccessful in reducing exposure-driven morbidity on the alert day. These results, again, are not surprising given the lack of reductions in pollution during pre-reform alerts. If the alerts are not being effective in improving air quality, then alerts are just a sign of high pollution, which has adverse health effects-.

There are some additional policy lessons that can be extracted from the results. First, the alert is issued based on actual ozone levels and not on forecasts, in contrast with air quality alert systems in other countries. Hence, once the alert is issued, the peak on other particles has passed and exposure has occurred (Figures 8 and 9).

Table 3: **Impacts of air quality alerts on health : Pre-Reform.**

	(1)	(2)	(3)	(4)	(5)	(6)
	Respiratory	**Respiratory**	**Asthma**	**Asthma**	**CVD**	**CVD**
	All	$<$5 and $>$65	All	$<$5 and $>$65	All	$<$5 and $>$65
$t=-4$	-0.0223*	-0.0171	-0.00184	-0.00339	0.00145	0.00807
	(0.0116)	(0.0115)	(0.0110)	(0.0105)	(0.0115)	(0.0124)
$t=-3$	-0.0171	-0.0119	0.00225	0.00804	0.00155	0.00332
	(0.0116)	(0.0115)	(0.0109)	(0.0105)	(0.0108)	(0.0107)
$t=-2$	-0.0165	-0.0139	0.0152	0.0252**	-0.00201	-0.00504
	(0.0106)	(0.0105)	(0.0107)	(0.0107)	(0.0106)	(0.0104)
$t=-1$	-0.00633	-0.00799	0.00792	0.0128	-0.00441	0.00766
	(0.0103)	(0.00994)	(0.0103)	(0.0101)	(0.0107)	(0.0108)
$t=0$	0.0131*	0.00529	-0.00726	-0.0161**	-0.00415	-0.00677
	(0.00674)	(0.00660)	(0.00660)	(0.00647)	(0.00666)	(0.00657)
$t=1$	0.0150	0.00827	-0.00656	-0.00689	-0.0102	-0.0108
	(0.00914)	(0.00897)	(0.00836)	(0.00838)	(0.00824)	(0.00832)
$t=2$	0.0208**	0.0112	-0.00598	-0.00973	-0.00537	-0.00921
	(0.0105)	(0.0113)	(0.00852)	(0.00950)	(0.00836)	(0.00820)
$t=3$	0.0212**	0.0190*	0.0149	0.0125	0.00532	0.00500
	(0.0103)	(0.0106)	(0.00965)	(0.0101)	(0.00904)	(0.00962)
$t=4$	0.0117	-0.00149	0.0323***	0.0248**	-0.00234	0.000721
	(0.0102)	(0.0101)	(0.0118)	(0.0121)	(0.0103)	(0.0106)
N	964,033	964,033	964,033	964,033	964,033	964,033
Seasonal Controls	✓	✓	✓	✓	✓	✓
$\widehat{API}$	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: Table shows the impacts of a PCAA alert on ER visits. The coefficients α_t's are coefficients of the relative time dummy variables, where $t = j - j_{start}$. Instrumented air pollution index is included with four lags. All variables are seasonally adjusted. Data is obtained from patient-level anonymized hospital records from all public hospitals in CDMX. CVD=Cardiovascular disease. Seasonal and pollution controls are obtaining matching each hospital with the three closest meteorological stations. This estimation assumes that people attend the hospital that is closest to their location during that day. Data is restricted to Jan 1st, 2011 to April 4th, 2016.

7.2 Post-reform

In section 6.2, I show that after the 2016 reform, PCAA alerts achieve large reductions in air pollution. Decreases in traffic-generated NO2 and CO drive these reductions. Large health benefits are thus expected. Short-term exposure to ambient NO2 has adverse effects on pulmonary function, particularly in asthmatics, impacting morbidity, hospital admissions, and mortality (Samoli et al., 2006). In a systematic review conducted by Mills et al. (2015), the authors find that for a 10 μg/m3 increase in 24-hour NO2 is associated with increases in all-cause, cardiovascular and respiratory mortality (0.71%, 0.88% and 1.09%, respectively), and with hospital admissions for respiratory (0.57%) and cardiovascular (0.66%) diseases. Similarly, both acute and chronic exposure to carbon monoxide are associated with increased risk for adverse cardiopulmonary events, including death (Chen et al., 2007). Knittel et al. (2016) show that even at current levels, CO has large marginal effects on weekly infant mortality rates, especially for premature or low birth-weight infants.

Table 4 shows the effects of PCAA alerts after the reform in April 2016. With the introduction of traffic and industry restrictions, the program's success in reducing pollution-driven hospital admissions increased significantly. There is a drop of 0.019 standard deviation in ER visits per hour per hospital on the alert day. This decrease represents 10% from the mean. The impacts are driven by children and the elderly, which see a -.02 standard deviation decrease in ER admissions (12.06% of the mean). The effects are strongest for asthma ER visits, that experience a reduction of 0.057 SD in visits per hour, per hospital. This decrease is equivalent to a reduction of 54%. The positive effects last for two to four days. These results are also displayed in Figure 12,, which is useful for visually highlighting the horizontal horizontal pre-trends before an alert. Panels c) and d) of this figure also show that, after a post-2016 alert, there is a gradual return to the mean, so that the effects take three to four days to disappear. These results stand in stark contrast with what was observed before the 2016 reform, shown in parts a) and b) of Figure 12.

8 Mechanisms

Once the activation of Phase I restricts car usage, people face a series of mobility choices. First, the restrictions operate between 10 am and 5 pm, so one option is to change their trip hours. The second option is to switch their transportation mode towards bike, subway, bus,

Table 4: **Impacts of air quality alerts on health: Post-Reform.**

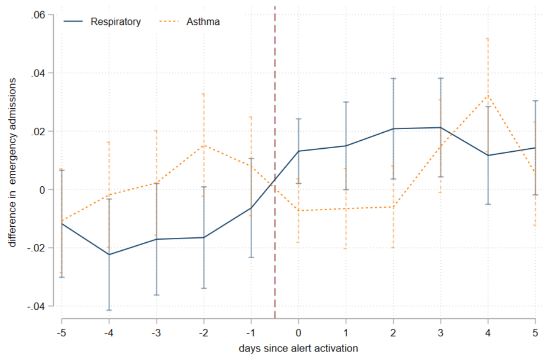
	(1)	(2)	(3)	(4)	(5)	(6)
	Respiratory	**Respiratory**	**Asthma**	**Asthma**	**CVD**	**CVD**
	All	<5 and >65	All	<5 and >65	All	<5 and >65
$t=-4$	-0.00539	-0.00882	0.00995	0.0111	0.0227	0.0169
	(0.0118)	(0.0116)	(0.0167)	(0.0140)	(0.0187)	(0.0197)
$t=-3$	0.00557	0.00821	0.00910	0.0238*	0.0202	0.0187
	(0.0100)	(0.0101)	(0.0142)	(0.0124)	(0.0176)	(0.0181)
$t=-2$	0.0113	0.00574	0.0264**	0.0107	0.0153	0.0111
	(0.00955)	(0.00973)	(0.0133)	(0.0119)	(0.0159)	(0.0158)
$t=-1$	0.000458	0.00415	0.00408	0.000302	0.0215	0.0174
	(0.00889)	(0.00903)	(0.0115)	(0.0113)	(0.0160)	(0.0162)
$t=0$	-0.0241***	-0.0238***	-0.0544***	-0.0330***	0.00173	-0.00889
	(0.00670)	(0.00660)	(0.0102)	(0.00895)	(0.0100)	(0.0101)
$t=1$	-0.0283***	-0.0293***	-0.0603***	-0.0301***	-0.000884	-0.00250
	(0.00788)	(0.00793)	(0.0106)	(0.00960)	(0.0117)	(0.0128)
$t=2$	-0.00624	-0.0109	-0.0394***	-0.0125	0.0128	0.0129
	(0.00878)	(0.00863)	(0.0109)	(0.0106)	(0.0130)	(0.0145)
$t=3$	-0.0115	-0.0126	-0.0258**	-0.00833	0.0174	-0.00179
	(0.00821)	(0.00827)	(0.0107)	(0.00954)	(0.0128)	(0.0130)
$t=4$	-0.0166*	-0.0216**	-0.0303***	-0.0137	0.0161	0.00816
	(0.00882)	(0.00866)	(0.0115)	(0.00992)	(0.0126)	(0.0139)
N	268,487	268,487	268,487	268,487	268,487	268,487
Seasonal Controls	✓	✓	✓	✓	✓	✓
API	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

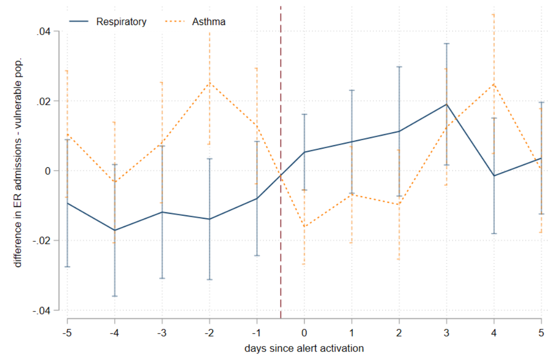
Note: Table shows the impacts of a PCAA alert on ER visits. The coefficients α_t's are coefficients of the relative time dummy variables, where $t = j - j_{start}$. Instrumented air pollution index is included with four lags. All variables are seasonally adjusted. Data is obtained from patient-level anonymized hospital records from all public hospitals in CDMX. CVD=Cardiovascular disease. Seasonal and pollution controls are obtaining matching each hospital with the three closest meteorological stations. This estimation assumes that people attend the hospital that is closest to their location during that day. Data is restricted from April 4th, 2016 to December 31st, 2017.

Figure 12: **Effect of PCAA activation on hospital emergency admissions**

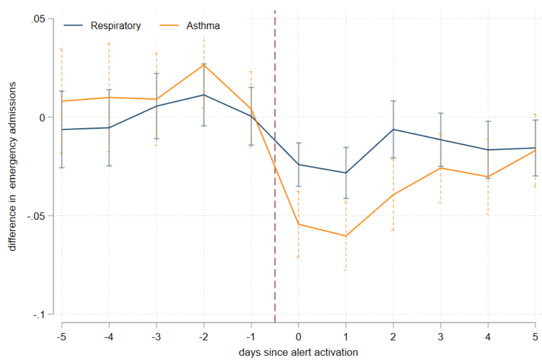
(a) Pre-reform: All admissions



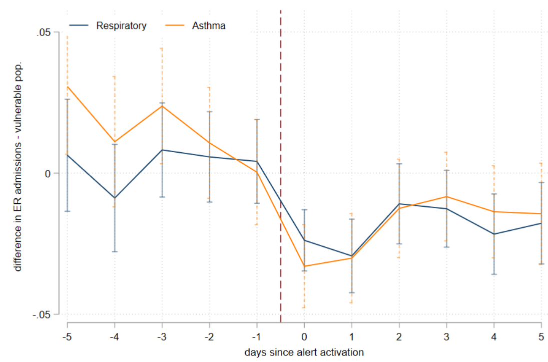
(b) Pe-reform : <5 and >65



(c) Post-reform: All admissions



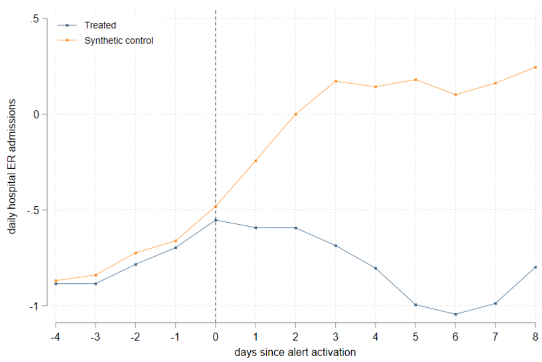
(d) Post-reform: <5 and >65



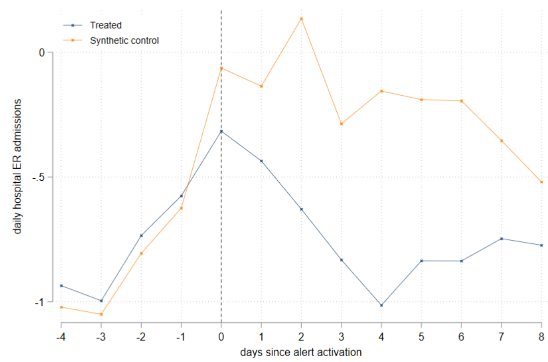
Note: This figure shows the trajectory of ER visits before and after the activation of an alert. This identification strategy controls for predicted pollution $\widehat{API}$, which is instrumented with wind speed and direction. This strategy seeks to isolate the policy-driven changes in hospital admissions. Seasonal fixed effects and weather controls are included. The sample is restricted to January 2013 to April 4th, 2016. Pollution data was obtained from monitor-level hourly readings. The Air Pollution Index (API) is constructed using the first component obtained from a principal component analysis of standardized NO2, CO, PM10, PM25, O3, and SO.

Figure 13: **Counterfactual of respiratory ER admissions - Post-reform**

(a) Post-reform: All respiratory



(b) Post-reform: Asthma



Note: This Figure shows the trajectory ER visits before and after the activation of an alert, denoted by Y_{kt}. The counterfactual $\hat{Y_{kt}^N}$ is estimated using a weighted average of other days in the sample. The covariates used to select from the donor pool are: previous ER visits, AQI, wind speed, temperature, and relative humidity. The period used for this selection are the five days previous to the activation of the alert. The sample is restricted from April 4th, 2016, to December 31st, 2017. Pollution data was obtained from monitor-level hourly readings. The Air Pollution Index (API) is constructed using the first component obtained from a principal component analysis of standardized NO2, CO, PM10, PM25, O3, and SO. Hospital-level pollution exposure is estimated by averaging the three closest monitoring stations walking, or carpooling. Third, there is the option of violating the restriction and risking paying a fine or a bribe. Finally, for the drivers that are allowed to drive, congestion levels in the city have changed, which may incentivize them to change their usual route.

In Section 6, I showed that there are significant reductions in traffic pollution: NO2 and CO. This section provides direct evidence on the mechanisms behind the mitigation, using data on traffic and public transportation use. First, I look at hourly changes in car usage patterns using traffic and speed data. Second, I look at the effect on the days before and after the alert to explore inter-day displacement of trips. Finally, I show that public transport use also decreases, suggesting that people stay more at home, potentially driving the strong positive health effects.

8.1 Car usage

In Section 2, I described the evidence of cheating and low enforcement for other environmental programs in Mexico. However, there are incentives to enforce the PCAA for two reasons. First, the fine for driving on a restricted day is up to 135 USD (2,4568 MXN), approximately 20 times the daily minimum wage. Additionally, the police take the car to the impound lot, which is also very costly for drivers since they are usually in the city's periphery. Second, even if these fines are not enforced, there is widespread bribing (Fried et al., 2010) in the streets, which accounts for almost half of the monthly income of local police (Vela, 2019). Hence, police officers have the incentive to pursue drivers that are violating PCAA. Finally, in contrast with the results in Davis (2008), people do not have an incentive to buy a car in anticipation of an alert - and the driving restrictions it entails-, because the alerts are unpredictable. They only happen a few times a year, and they are randomized so that a different subset of cars is restricted each time there is an alert.

Figure 14 shows the difference in average hourly car counts between PCAA and regular days, using the following specification:

$$count_{it} = \sum_{j=1}^{23} \zeta_j \mathbb{1}(hr_t = j) + \sum_{j=1}^{23} \eta_j \mathbb{1}(hr_t = j) * D_t + \theta_{it} + Xij\nu_{it} \tag{6}$$

Where η_j, the coefficient of the difference between PCAA days and regular days for hour $j = 1, ..., 23$ is the parameter of interest, plotted in figure 14 and 15. ζ_j are hour-of-day fixed effects, θ_{it} a set of time and location fixed effects, Xij are weather controls and ν_{it} robust standard errors. I only analyze the post-reform period, because data availability starts in 2016.

The area under the curve in Figure 14 suggests that once controlling for seasonal and environmental fixed effects, there is a net decrease of 105,884 cars on PCAA days. However, the alerts positively and significantly affect the number of vehicles counted per hour at two moments: rush hour (9 am and 8 pm) and unrestricted hours (before 5 am and after 10 pm). These effects have two different sources because congestion does not have a monotonic relationship with car counts. If there are fewer gridlocks during peak hours, this will increase the number of cars passing at those times. Increases in the car counts at un-restricted hours, which are late at night and usually not characterized by traffic jams, reflect real increases in the number of trips. Speed, on the other hand, does have a monotonic relationship with congestion. For this reason, in the urban planning and engineering literature, it is suggested that a traffic index should measure how much average speed declines during peak times (Qi et al., 2016).

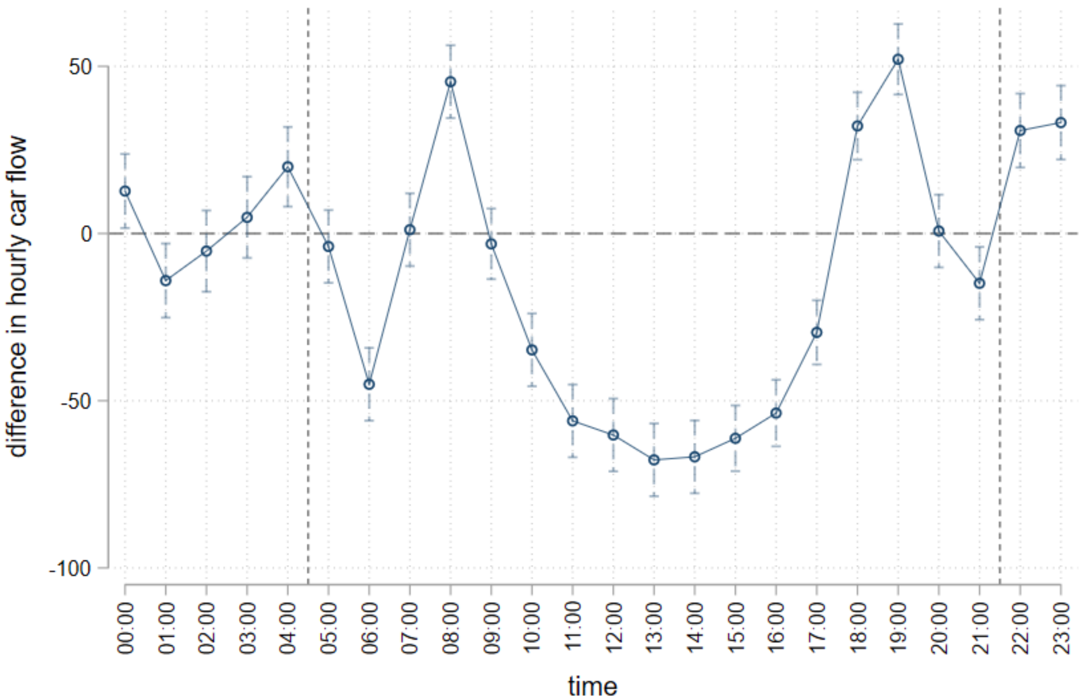
Using speed as my preferred measure of congestion, 15 shows a maximum increase of 2km/h, which means that an exogenous activation of the environmental alert entails a 5% increase in the average speed at rush hours. Interestingly, there is a clear, robust switching in travel times. Simultaneously analyzing Figure 14, and Figure 15 can shed some light on these changes. 10 pm -12 am, and 4 am show an increase in both the number of cars and the speed. Since midnight is not an hour with much congestion (see Figure A.8), this would suggest that more people waited until this time to go back home from work. The rest of the day has lower car counts and higher or similar speed, suggesting fewer cars in the streets.

With fewer cars in the street, there is a decrease in the total number of accidents during restricted hours (Figure 17). There is a decrease of up to 18% in the number of accidents per hour. The total reduction in road accidents in the city in PCAA days is 51.2.

8.2 Awareness

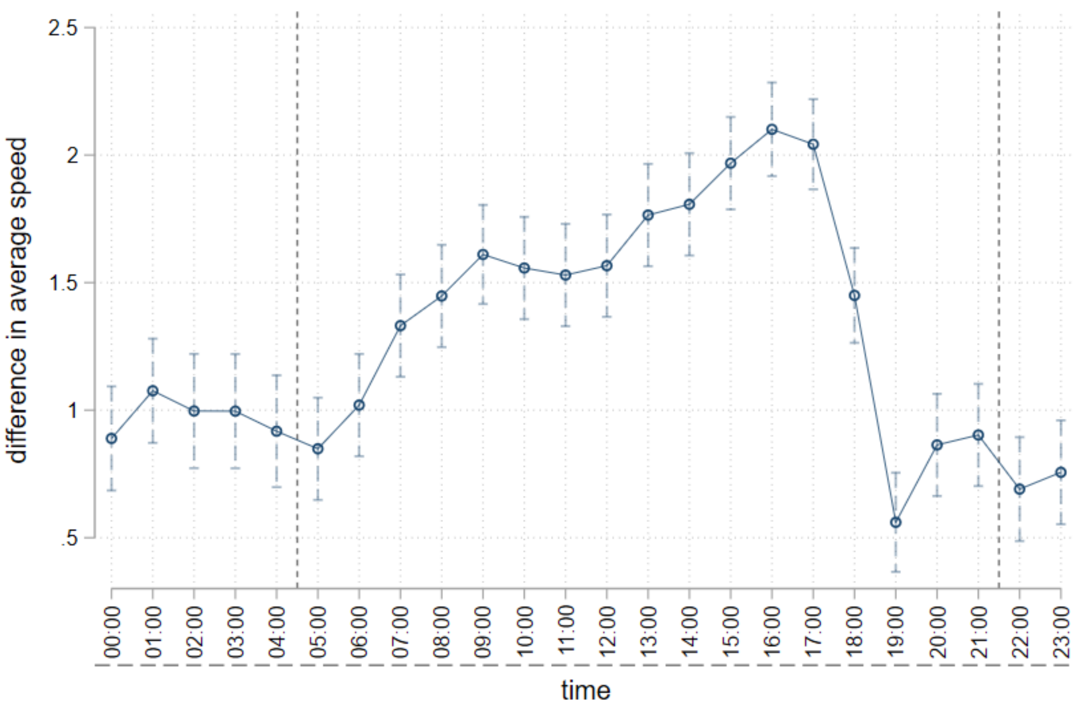
The evidence presented in previous sections indicates that the PCAA's effects changed after its 2016 reform. Alerts were mostly ineffective in reducing pollution and morbidity

Figure 14: **Difference in car counts, post-reform. (PCAA days - regular days)**.



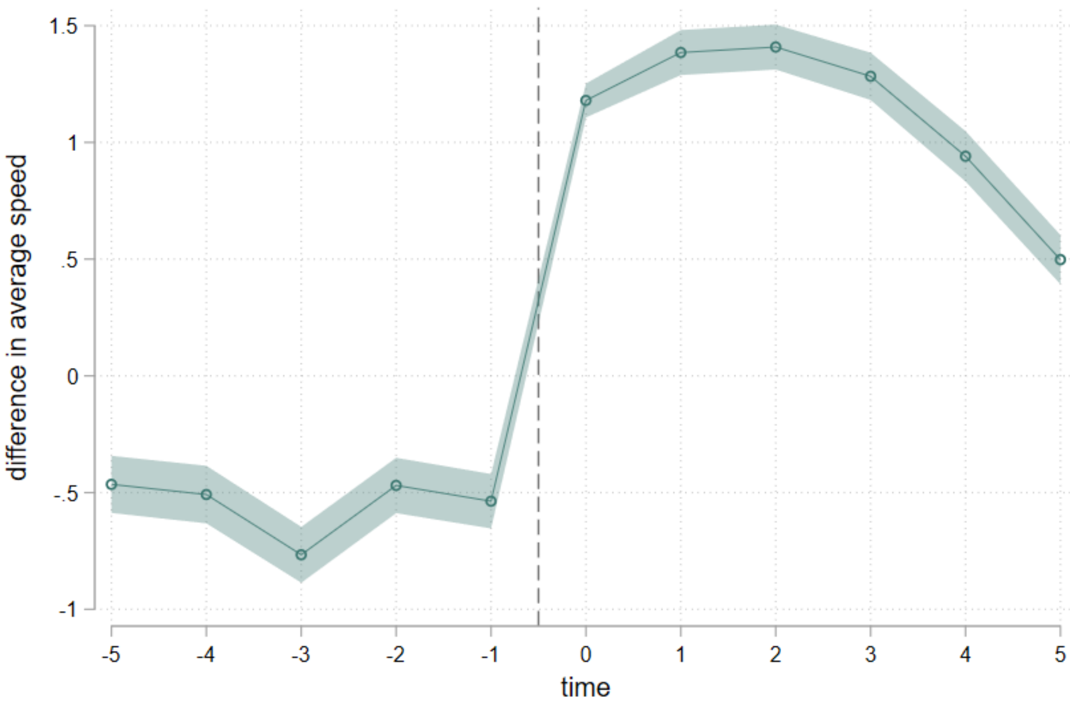
Note: Figure shows the average hour-of-day difference in car counts between PCAA and regular days. Seasonal fixed effects and weather controls are used. Sample is restricted from April 4th, 2016 to Dec 31st, 2019. Traffic data was obtained 343 sensors and video-detectors, mapped in Figure 4.

Figure 15: **Difference in average speed by hour, post-reform (PCAA days - regular days).**



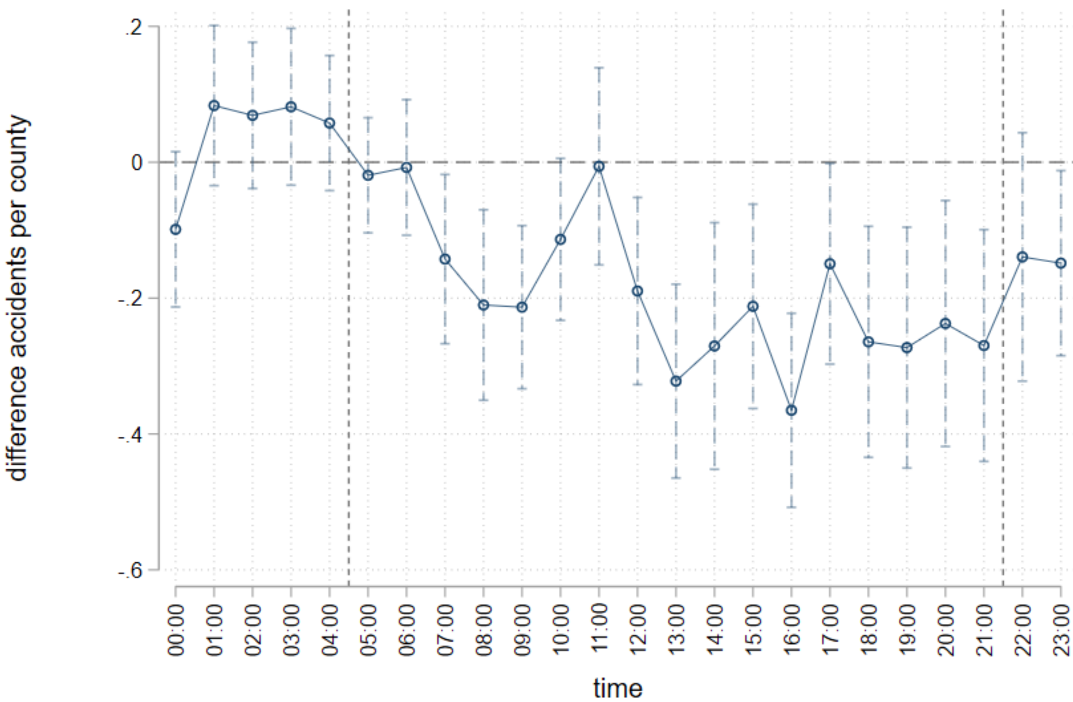
Note: Figure shows the average hour-of-day difference speed between PCAA and regular days. Seasonal fixed effects and weather controls are used. Sample is restricted from April 4th, 2016 to Dec 31st, 2019. Traffic data was obtained 343 sensors and video-detectors, mapped in Figure 4.

Figure 16: **Impact on PCAA alerts on congestion: daily effects, post-reform**



Note: Figure shows the trajectory of the difference in average speed before and after the activation of an alert using a generalized difference in difference (event-study) approach. Seasonal fixed effects and weather controls are used. Sample is restricted from April 4th, 2016 to Dec 31st, 2019. Traffic data was obtained 343 sensors and video-detectors, mapped in Figure 4

Figure 17: **Impact of PCAA on accidents, post-reform**



Note: Figure shows the average hour-of-day difference in road accidents between PCAA and regular days. Seasonal fixed effects and weather controls are used. Sample is restricted from April 4th, 2016 to Dec 31st, 2019. Road accident data was obtained from administrative police records.

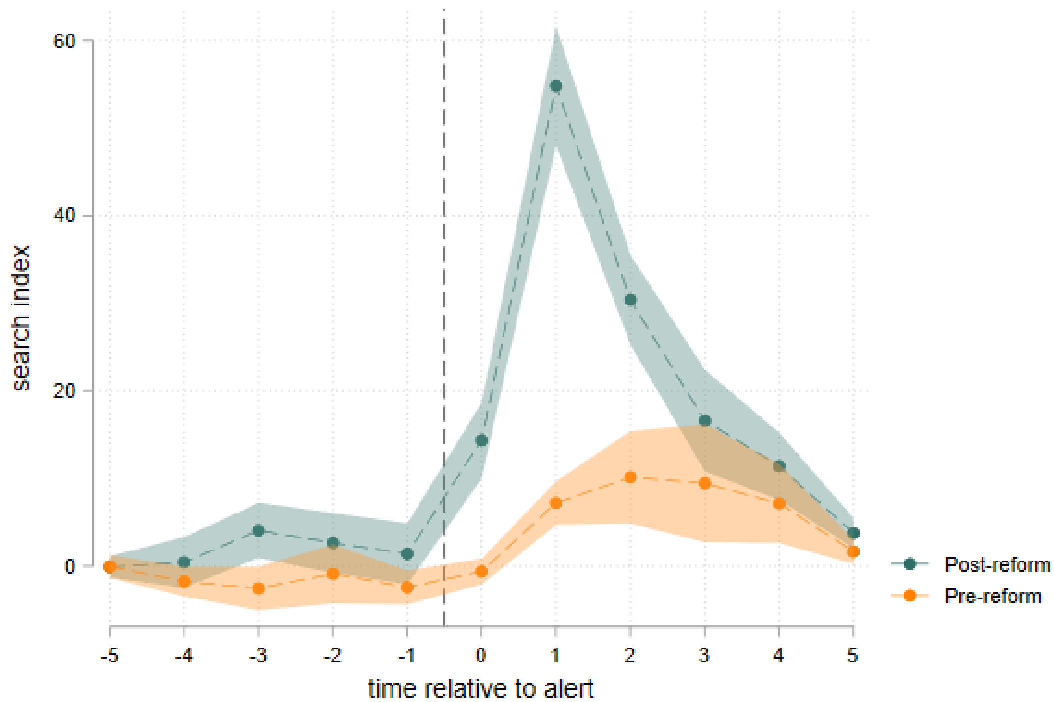
until the additional restrictions were introduced. However, when looking at each alert, the results show that people react before the actual restrictions kick in: both air quality and health improvements begin on the afternoon of the alert, while driving restrictions start the next morning. In Section 8.1, I showed that considerable reductions in congestion happen immediately after the alert is issued and that this is most likely due to a decrease in discretionary trips since the alert is announced.

In this section, I show that the mitigation component of the alert that entered in 2016 made the warnings more salient, generating an increased interest – measured using Google searches– in both the PCAA program and air pollution in general.

Using daily search data from Google Trends, Figure 18 shows a slow and small, but statistically significant increase in interest in the PCAA program on alert days before the reform (in orange). The size of the effect after the reform (in blue) is six times the pre-2016 effect. Interestingly, after the reform, the impact on awareness starts on the day the alert is issued, even though driving restrictions begin on the next morning. This pattern is similar to the effects on car usage: there is a considerable effect on the first day, but it is surpassed by the second day. Figure 19 shows that the impact on an alert after the reform on interest in air quality (in blue) is almost three times the effect that the policy had before the reform (in orange), and nearly twice the effect on the second day.

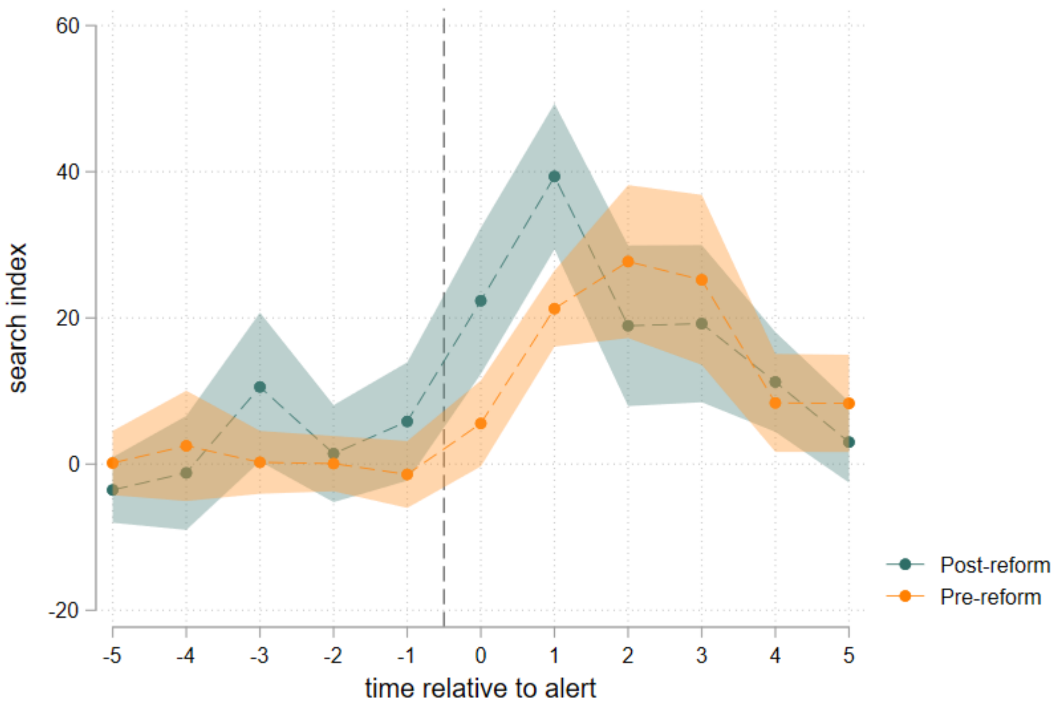
I also used public subway and bus rapid transport (BRT) data to assess whether this increased awareness translated into switching from car usage to public transportation. However, I find no robust effects of the policy in subway or BRT usage, which could be because the data is not representative of the full transportation patterns in the city. Most of the population that does not move by car, moves by minibus or bus (not BRT), for which no data exists. However, the timing of the effects of car usage –before the restrictions enter into place– and the increased awareness about pollution that occurs after the reform, are suggestive evidence that the policy does foster some avoidance behavior in people. They are more aware about pollution and they reduce their discretionary trips as soon as the policy is announced.

Figure 18: **Interest/awareness of the PCAA**



Note: Figure shows the search index in Google Trends for the word *contingencia*(the name of the alert in Spanish). Data from 2013 to 2019. Search results are normalized to the time and location of a query. Seasonal and fixed effects are included. Data is restricted to Mexico City.

Figure 19: **Interest/awareness of pollution**



Note: Figure shows the search index in Google Trends for the term *air quality*. Data from 2013 to 2019. Search results are normalized to the time and location of a query. Seasonal and fixed effects are included. Data is restricted to Mexico City.

9 Conclusions

With large manifestations of environmental degradation already affecting the lives of millions of people around the world, the interactions between mitigation and adaptation policies have acquired great theoretical and practical relevance. Standard economic analyses of environmental policy focus on either mitigation or adaptation. In response to real-world complexity and the urgency of mitigating the health effects of environmental insults, policymakers have taken a multi-pronged approach that pairs information provision with short and long-run mitigation actions. This paper studies one widely used example of such a policy— air quality alerts.

Exposure to air pollution has substantial negative impacts on human health, even in the very short run. Consequently, while navigating politically complex long-run solutions to improve air quality, city governments worldwide have increasingly adopted air quality warnings as a measure to reduce the health impacts of very polluted days. These programs are especially relevant in regions where extreme pollution levels accompany rapid and often disorganized urbanization. Decision-makers face a double bind if they want to implement short-run mitigation and information policies: past research has shown that there could be trade-offs between these two approaches. In this paper, I explore whether information policy is more effective when paired with mitigation. To answer this question, I study a program that, before 2016, provided only information about high pollution levels in the form of alerts. In 2016, the policy was changed: warnings were issued at the same pollution levels, but now mitigation measures were undertaken. I use hospital-level health outcomes matched to monitor-level pollution and weather data to estimate its pollution and health effects. I use sensor-level traffic data, geo-tagged accident reports, and social network data to unveil the mechanisms through which considerable short-run improvements in air quality and health are achieved after issuing an alert.

I find that before the 2016 reform, the policy does not improve air quality. However, the program has strong same-day effects after 2016: a cumulative reduction of more than seven times the pollution index's hourly standard deviation. The license-plate based driving restrictions only operate between 5 am and 10 pm, and the effect estimates reflect these hourly patterns. There is an increase in pollution in the second day after the alert. Despite the night-time and second-day increases in pollution, the net cumulative exposure is reduced in 2.5 standard deviations. I find that reductions in NO2 and CO, which are most closely linked to the transport sector, drive the mitigation outcomes. PM10 and SO2, which are more linked to other urban processes and activities, remain mostly unaffected by the policy.

I also find that the policy's effect on ER visits happens exclusively after the driving and industry restrictions were introduced in 2016, suggesting that the mitigation component is critical in achieving public health benefits. On a typical alert issued after the 2016 reform, there is a decrease of 11% in ER visits. The impacts are driven by reductions in ER visits by children and the elderly, who experience a 12% decrease in ER admissions. The effects are most substantial for asthma, with a 54% reduction. The policy is successful in changing behavior. Using average vehicle speed and car counts as complementary road traffic measures, I find that car usage decreases significantly after an alert is issued. The average speed in the city increases up to 5%. Car counts decrease by up to 18%. Emptier streets also have significant co-benefits: there is a decrease of up to 18% in the number of accidents per hour. The total reduction in road accidents in the city in PCAA days is 51.2.

This paper contributes to our knowledge of a central tension in environmental policy: balancing the marginal damage of pollution with the marginal abatement costs. Because of the several potential trade-offs, more research is needed on the interaction of adaptation and mitigation policies. I find that the mitigation component is crucial to achieve the health effects of the PCAA alerts. My findings also contribute to the information and protective behavior literature and, more specifically, to the air quality warnings literature, which has mostly overlooked programs that include mitigation (See Neidell (2009); Welch et al. (2005); Saberian et al. (2017) and Tribby et al. (2013)), and has found mixed results on their effectiveness.

I also contribute to the quasi-experimental literature in economics on the health effects of air pollution.[13] I show that the concentration of high pollution levels over time, rather than merely their aggregate amount, may be essential in determining the health damages generated from it. So, generating discontinuities in exceptionally high pollution levels may help improve health outcomes, even if emissions aggregated over a longer time interval are only modestly affected. My results also contrast with past literature that has found

[13](Most papers in this literature look at infant mortality. See Chay et al. (2003); Currie and Neidell (2005); Currie et al. (2009b); Chen et al. (2013); Deschenes et al. (2017); Schlenker and Walker (2015) and Deryugina et al. (2019) for some exceptions.

that license-plate based driving restrictions are ineffective for long-run pollution mitigation (Davis, 2008). Hence, a second policy implication is that anticipation of restrictions is a crucial element in policy ineffectiveness.

The policy's post-reform health effects have three potential channels: a) reductions in pollution, b) displacement in pollution, which produces a more staggered exposure, and c) salience of the policy. This third channel would imply that after 2016, driving and industry restrictions make the policy more salient. The enforcement efforts could be a potential driver of the policy's change in awareness, incentivizing people to take more protective measures. In this paper, I show evidence of these three mechanisms happening. I find evidence that people stay at home more on alert days and that the mitigation component makes the overall policy more salient, potentially boosting adaptation strategies. Further research – both in public health and economics- is also needed to disentangle these mechanisms and determine which one drives the bulk of the health effects. These insights will be relevant in informing policymakers on strategies to achieve health improvements in the most cost-effective way.

My findings are especially relevant because temporary additional driving restrictions have become a commonly used tool in Mexico to restrict mobility in response to public health emergencies. During wildfires in 2019 and the first part of the COVID-19 pandemic, Mexico City's government imposed the temporary driving restrictions that are usually associated with PCAA alerts. Other city governments followed and applied similar measures. In the US, several municipalities implemented driving restrictions to limit non-essential trips during the pandemic.

References

Abadie, A., Diamond, A., and Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American statistical Association*, 105(490):493–505.

Abadie, A., Diamond, A., and Hainmueller, J. (2015). Comparative politics and the synthetic control method. *American Journal of Political Science*, 59(2):495–510.

Anderson, M. L. (2014). Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. *American Economic Review*, 104(9):2763–96.

Arceo, E., Hanna, R., and Oliva, P. (2016). Does the effect of pollution on infant mortality differ between developing and developed countries? evidence from mexico city. *The Economic Journal*, 126(591):257–280.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., and Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, 124(1):105–159.

Barwick, P. J., Li, S., Lin, L., and Zou, E. (2019). From fog to smog: The value of pollution information. Technical report, National Bureau of Economic Research.

Chang, T., Graff Zivin, J., Gross, T., and Neidell, M. (2016). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy*, 8(3):141–69.

Chay, K., Dobkin, C., and Greenstone, M. (2003). The clean air act of 1970 and adult mortality. *Journal of risk and uncertainty*, 27(3):279–300.

Che, W., Frey, H. C., and Lau, A. K. (2016). Sequential measurement of intermodal variability in public transportation pm2. 5 and co exposure concentrations. *Environmental science & technology*, 50(16):8760–8769.

Chen, T.-M., Kuschner, W. G., Gokhale, J., and Shofer, S. (2007). Outdoor air pollution: nitrogen dioxide, sulfur dioxide, and carbon monoxide health effects. *The American journal of the medical sciences*, 333(4):249–256.

Chen, Y., Ebenstein, A., Greenstone, M., and Li, H. (2013). Evidence on the impact of sustained exposure to air pollution on life expectancy from china's huai river policy. *Proceedings of the National Academy of Sciences*, 110(32):12936–12941.

Cruz, F. and Garza, G. (2014). Configuración microespacial de la industria en la ciudad de méxico a inicios del siglo xxi. *Estudios demográficos y urbanos*, 29(1):9–52.

Currie, J., Hanushek, E. A., Kahn, E. M., Neidell, M., and Rivkin, S. G. (2009a). Does pollution increase school absences? *The Review of Economics and Statistics*, 91(4):682–694.

Currie, J. and Neidell, M. (2005). Air pollution and infant health: what can we learn from california's recent experience? *The Quarterly Journal of Economics*, 120(3):1003–1030.

Currie, J., Neidell, M., and Schmieder, J. F. (2009b). Air pollution and infant health: Lessons from new jersey. *Journal of health economics*, 28(3):688–703.

Cutter, W. B. and Neidell, M. (2009). Voluntary information programs and environmental regulation: Evidence from spare the air. *Journal of Environmental Economics and management*, 58(3):253–265.

Davis, L. W. (2008). The effect of driving restrictions on air quality in mexico city. *Journal of Political Economy*, 116(1):38–81.

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., and Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review*, 109(12):4178–4219.

Deschenes, O., Greenstone, M., and Shapiro, J. S. (2017). Defensive investments and the demand for air quality: Evidence from the nox budget program. *American Economic Review*, 107(10):2958–89.

Foster, A., Gutierrez, E., and Kumar, N. (2009). Voluntary compliance, pollution levels, and infant mortality in mexico. *American Economic Review*, 99(2):191–97.

Fried, B. J., Lagunes, P., and Venkataramani, A. (2010). Corruption and inequality at the crossroad: A multimethod study of bribery and discrimination in latin america. *Latin American Research Review*, pages 76–97.

Galiani, S. and Quistorff, B. (2017). The synth_runner package: Utilities to automate synthetic control estimation using synth. *The Stata Journal*, 17(4):834–849.

Gallego, F., Montero, J.-P., and Salas, C. (2013). The effect of transport policies on car use: Evidence from latin american cities. *Journal of Public Economics*, 107:47–62.

Graff Zivin, J. and Neidell, M. (2012). The impact of pollution on worker productivity. *American Economic Review*, 102(7):3652–73.

Graff Zivin, J. and Neidell, M. (2013). Environment, health, and human capital. *Journal of Economic Literature*, 51(3):689–730.

Greenstone, M. and Jack, B. K. (2015). Envirodevonomics: A research agenda for an emerging field. *Journal of Economic Literature*, 53(1):5–42.

Hanna, R. and Oliva, P. (2015). The effect of pollution on labor supply: Evidence from a natural experiment in mexico city. *Journal of Public Economics*, 122:68–79.

Juan Lopez, M., Martinez Valle, A., and Aguilera, N. (2015). Reforming the mexican health system to achieve effective health care coverage. *Health Systems & Reform*, 1(3):181–188.

Knittel, C. R., Miller, D. L., and Sanders, N. J. (2016). Caution, drivers! children present: Traffic, pollution, and infant health. *Review of Economics and Statistics*, 98(2):350–366.

Lavy, V., Ebenstein, A., and Roth, S. (2012). The impact of air pollution on cognitive performance and human capital formation. *Unpublished. http://www2. warwick. ac. uk/fac/soc/economics/staff/academic/lavy/text_ and_ tables_ air_ pollution_ draft_ 20_ 09_ 12. pdf.*

Lin, C.-Y. C., Zhang, W., and Umanskaya, V. I. (2011). The effects of driving restrictions on air quality: São paulo, bogotá, beijing, and tianjin. Technical report.

McDermott, G. R., Meng, K. C., McDonald, G. G., and Costello, C. J. (2019). The blue paradox: Preemptive overfishing in marine reserves. *Proceedings of the National Academy of Sciences*, 116(12):5319–5325.

Mills, I. C., Atkinson, R. W., Kang, S., Walton, H., and Anderson, H. (2015). Quantitative systematic review of the associations between short-term exposure to nitrogen dioxide and mortality and hospital admissions. *BMJ open*, 5(5).

Moretti, E. and Neidell, M. (2011). Pollution, health, and avoidance behavior evidence from the ports of los angeles. *Journal of human Resources*, 46(1):154–175.

Neidell, M. (2009). Information, avoidance behavior, and health the effect of ozone on asthma hospitalizations. *Journal of Human resources*, 44(2):450–478.

Neidell, M. (2010). Air quality warnings and outdoor activities: evidence from southern california using a regression discontinuity design. *Journal of Epidemiology & Community Health*, 64(10):921–926.

Oliva, P. (2015). Environmental regulations and corruption: Automobile emissions in mexico city. *Journal of Political Economy*, 123(3):686–724.

Qi, H., Liu, M., Zhang, L., and Wang, D. (2016). Tracing road network bottleneck by data driven approach. *PloS one*, 11(5).

Rittenhouse, K. and Zaragoza-Watkins, M. (2018). Anticipation and environmental regulation. *Journal of Environmental Economics and Management*, 89:255–277.

Saberian, S., Heyes, A., and Rivers, N. (2017). Alerts work! air quality warnings and cycling. *Resource and Energy Economics*, 49:165–185.

Sachar, S., Campbell, I., and Kalanki, A. (2018). Solving the global cooling challenge: How to counter the climate threat from room air conditioners.

Samoli, E., Aga, E., Touloumi, G., Nisiotis, K., Forsberg, B., Lefranc, A., Pekkanen, J., Wojtyniak, B., Schindler, C., Niciu, E., et al. (2006). Short-term effects of nitrogen dioxide on mortality: an analysis within the aphea project. *European Respiratory Journal*, 27(6):1129–1138.

Schlenker, W. and Walker, W. R. (2015). Airports, air pollution, and contemporaneous health. *The Review of Economic Studies*, 83(2):768–809.

Shrader, J. (2020). Expectations and adaptation to environmental risks. *Available at SSRN 3212073*.

Tribby, C. P., Miller, H. J., Song, Y., and Smith, K. R. (2013). Do air quality alerts reduce traffic? an analysis of traffic data from the salt lake city metropolitan area, utah, usa. *Transport Policy*, 30:173–185.

Vela, R. (2019). "gano 16 mil pesos al mes y como otros 14 en sobornos": policías de tránsito de la cdmx.

Viard, V. B. and Fu, S. (2015). The effect of beijing's driving restrictions on pollution and economic activity. *Journal of Public Economics*, 125:98–115.

Welch, E., Gu, X., and Kramer, L. (2005). The effects of ozone action day public advisories on train ridership in chicago. *Transportation Research Part D: Transport and Environment*, 10(6):445–458.

Zhang, W., Lawell, C.-Y. C. L., and Umanskaya, V. I. (2017). The effects of license plate-based driving restrictions on air quality: Theory and empirical evidence. *Journal of Environmental Economics and Management*, 82:181–220.

Appendix

a) Measures of the PCAA

Figure A.1: **The PCAA. Measures and Phases**

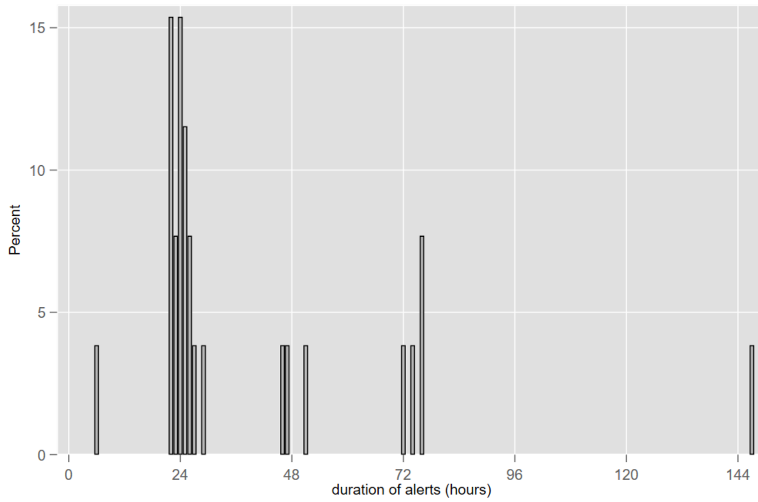
	PRE-CONTINGENCY	PHASE 1 (2016)	PHASE 2
OVERALL POPULATION	***Recommendations:***		
	Reduce the time spent outdoors		
	Reduce LP gas consumption		
		Report fires and gas leaks to the corresponding authorities	
		Carpooling and home office are recommended	
	Mandatory actions or restrictions:		
	Fires and open fires are not allowed		
		Suspend outdoor activities in all schools	
			Cancel activities in public institutions
			Cancel classes in private and public schools
TRANSPORT	No vehicles for publicity purposes		
		Additional age -and emissions- based driving restrictions are added to HNC*	
			Stronger additional vehicular restrictions than in Phase 1
BUSINESS & SERVICES	Suspend activities that generate fugitive emissions from VOC		
	Suspend activities in establishments that use wood or coal		
	Suspend all construction, remodeling, demolition and movement activities		
		Stop operation at gasoline stations that do not have return systems for petrol fumes	
AUTHORITIES	Suspend infrastructure maintenance, including paving		
	Strengthen the monitoring and combat of fires in agricultural and forest areas		
	Strengthen the surveillance and fines of vehicles and establishments who fail to comply with the respective measures		
	Suspend activities that involve ceramic or brick baking and melting furnace		

* Regular "Hoy No Circula" (HCN) restrictions are based on the age and the emissions of the vehicle and they have a specific day to not transit. In emergencies, restrictions for older and more pollutant vehicles are tougher. Since 2019, additional restrictions are the same in Phase I and Phase II

Note: Table shows a summarized version of the most relevant measures of the Mexico City Environmental Alerts Program (PCAA). In 2016, Pre-warnings were eliminated from the program and all the measures in the Panel 1) in the Table were included in Phase 1. This table was produced summarizing the official Mexico City Gazettes, available online.

b) Alerts duration and criteria pollutants

Figure A.2: **Histogram of alerts since 2016 by duration**

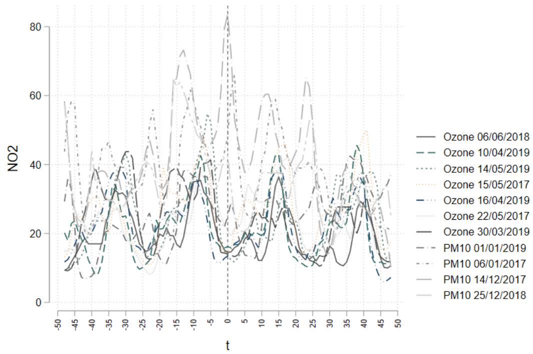


Note: The figure shows the distribution of alerts by their duration, measured in hours between activation and deactivation. Once the alert is active, a monitoring committee is in charge of determining when pollution and weather conditions allow to deactivate the alert. The figure shows substantial bunching in the duration of the alerts: most of them last around 24-27 hours (41%), with the rest lasting approximately 48 hours or approximately 72 hours. Data for this graph was obtained from the Atmospheric Monitoring System (SIMAT), which has an online reposed with information on each alert's timing and measures comes from a historical account of all the alerts issued since 1996 and a detailed list of all the modifications made to the program since then.

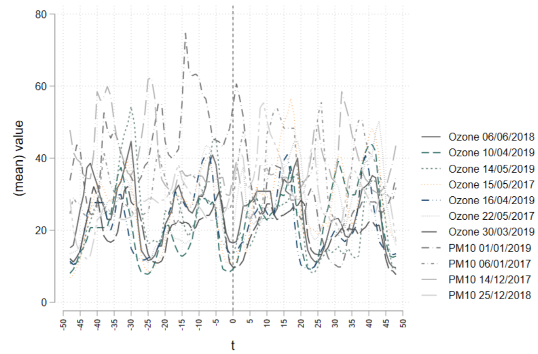
c) Typical evolution of an alert

Figure A.3: **Typical progress of an alert: NO2 and CO.**

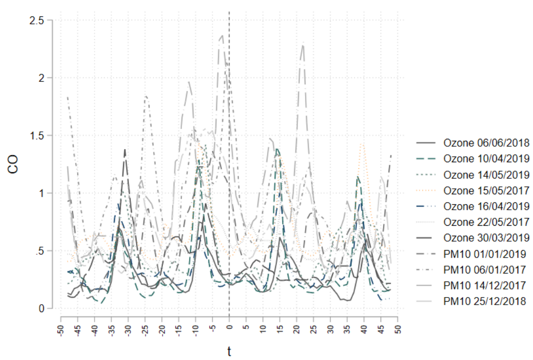
(a) NO2 and alerts



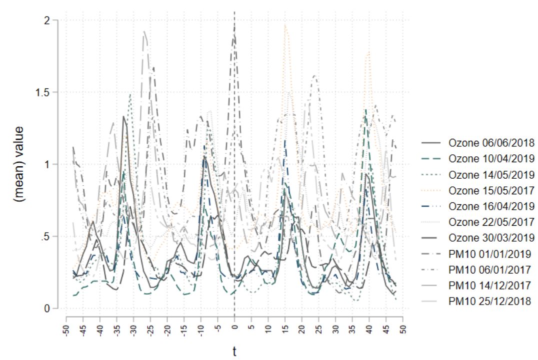
(b) NO2- 2 weeks later



(c) CO and Alerts



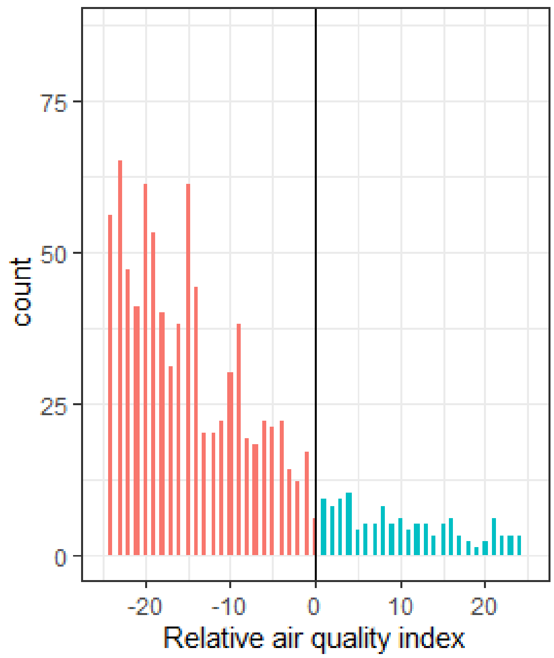
(d) CO- 2 weeks later



Note: The figure compares NO2 and CO trajectory on the 48 hours before and after a PCAA alert in Panel a). Only warnings between 2017 and 2019 are included in this figure. Panel b) shows the evolution of pollution two weeks (336 hours) after each alert. Monitor-level data was obtained from the Atmospheric Monitoring System (SIMAT), covering January, 2016-August, 2019, in Mexico City. From the same source, information on each alert's timing and measures comes from a historical account of all the alerts issued since 1996 and a detailed list of all the modifications made to the program since then.

d) Continuity test: probability of an alert

Figure A.4: **Visual continuity test:** days per level of relative index (where an alert should be active if relative index> 0)



Note: This figure shows the distribution of the ozone index around the threshold of activation. An alert should be active if the index is greater or equal than zero. The figure highlights that there is no apparent bunching right below zero. Hence, there is little concern about manipulation of the score and non-random activation of the policy.

e) Air Pollution Index

The Principal Component Analysis (PCA) is a mathematical procedure that transforms several possibly correlated variables into a smaller number of uncorrelated variables called principal components.This is, it is a dimensionality reduction tool. The first principal component accounts for as much data variability as possible, and each succeeding component accounts for as much of the remaining variability as possible. Variation in different particles is combined using PCA, Figure A.5 shows the screeplot resulting from the PCA and Table A.1 the contribution of each particle to the construction of the API.

Figure A.5: Scree plot after PCA

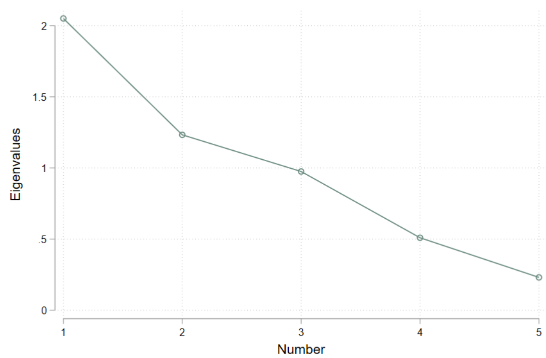


Table A.1: **Scoring coefficients**

Particle	1^{st} Component
Carbon monoxide (CO)	0.631
Nitrogen Dioxide (NO2)	0.621
Ozone (O3)	-0.068
Fine Particles (PM10)	0.456
Sulfur dioxide (SO2)	0.062

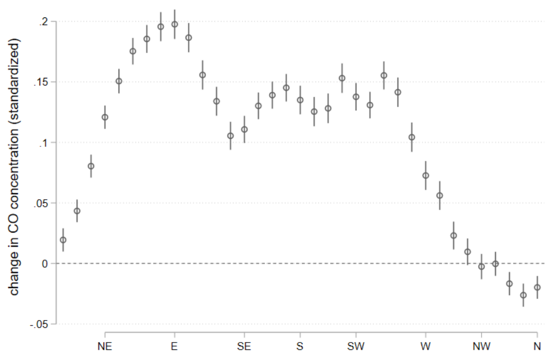
Note: All variables are corrected for seasonality

Air quality index = first component of PCA on particle concentrations. Explains 41% of the seasonally-corrected variation in pollution.

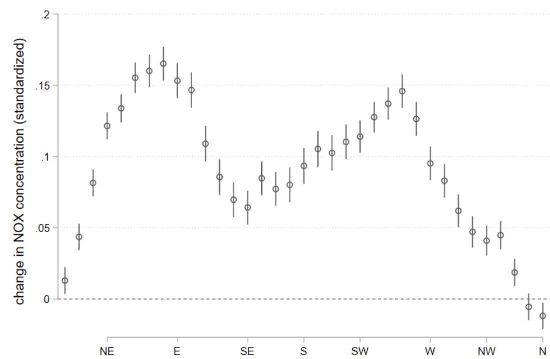
f) Wind direction and pollution in Mexico City

Figure A.6: Relationship between wind direction and pollution

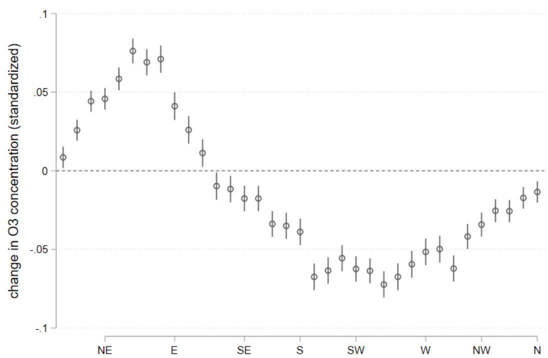
(a) CO 8 hour average



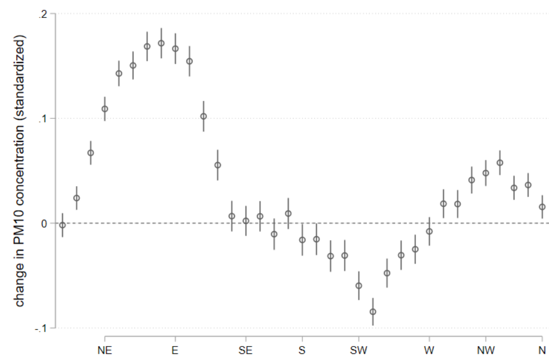
(b) NOX 8 hour average



(c) O3 8 hour average

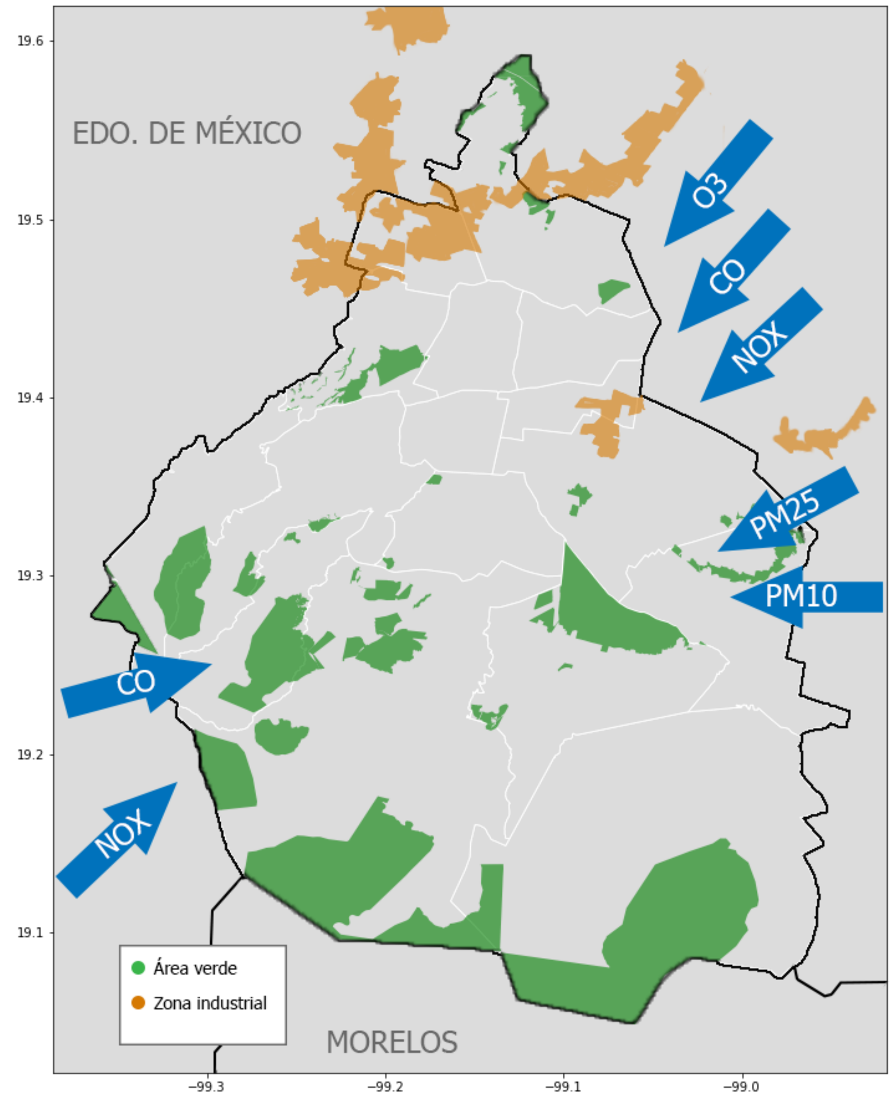


(d) PM10 8 hour average



Note: The figure shows the correlation between wind direction and pollution concentrations. The dependent variable is the 8-hour average of pollution, standardized and seasonally adjusted, including year, month, month-by-year, day-of-the year, time, and location fixed effects. 10-degree bins are used to measure wind direction flexibly. Second-degree polynomials of temperature, wind speed, relative humidity, as well as their interactions are included. The sample is restricted to January 2016 to December 2019. Pollution and weather data were obtained from monitor-level hourly readings.

Figure A.7: **Wind direction and air pollution:** Visual Illustration of city wide averages



Note: The figure illustrates the information in Figure A.6, on the predominant source of wind-driven pollution for each particle including CO, NOX, ozone, PM10 and PM25. The sample is restricted to January 2016 to December 2019. Pollution and weather data were obtained from monitor-level hourly readings. Green areas and industrial zones are marked in the map for reference. Green areas information was obtained from the city's Open Data Portal. Industrial zones shapefiles are obtained from (Cruz and Garza, 2014)

g) First stage table: wind speed, wind directio and pollution

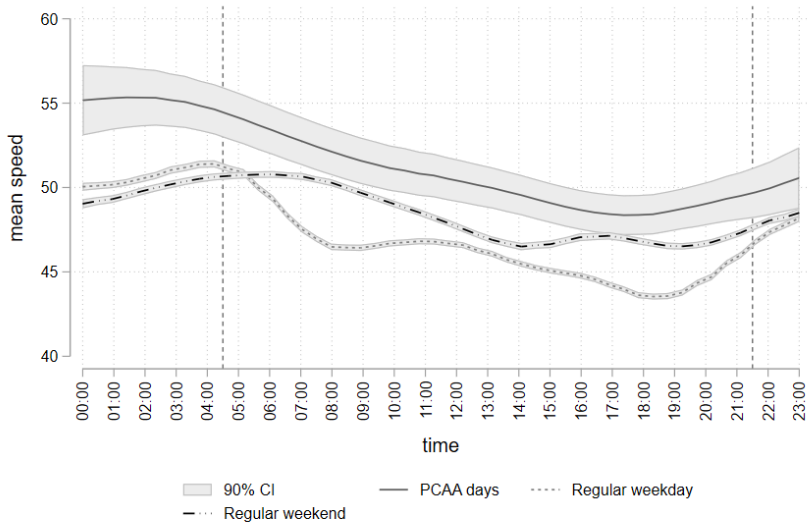
Table A.2: First stage results: impact of wind speed and wind direction on pollution

	(1)	(2)	(3)	(4)	(5)	(6)
	API		API		API	
	coef	se	coef	se	coef	se
Bin 4			-0.323***	0.0633	1.508***	0.0308
Bin 5			-0.181***	0.0608	1.443***	0.0256
Bin 6			0.184***	0.0622	1.433***	0.0228
Bin 7			0.471***	0.0619	1.585***	0.0196
Bin 8			0.979***	0.0630	1.659***	0.0215
Bin 9			1.166***	0.0611	1.611***	0.0174
Bin 10			1.482***	0.0606	1.726***	0.0163
Bin 11			1.533***	0.0602	1.746***	0.0151
Bin 12			1.601***	0.0598	1.724***	0.0137
Bin 13			1.607***	0.0596	1.669***	0.0133
Bin 14			1.573***	0.0594	1.634***	0.0125
Bin 15			1.485***	0.0592	1.534***	0.0116
Bin 16			1.531***	0.0592	1.573***	0.0115
Bin 17			1.508***	0.0591	1.561***	0.0108
Bin 18			1.382***	0.0590	1.447***	0.0103
Bin 19			1.308***	0.0589	1.377***	0.0101
Bin 20			1.256***	0.0589	1.325***	0.00999
Bin 21			1.179***	0.0589	1.280***	0.00989
Bin 22			1.053***	0.0590	1.170***	0.0103
Bin 23			0.938***	0.0589	1.084***	0.0102
Bin 24			0.870***	0.0590	1.056***	0.0109
Bin 25			0.793***	0.0591	1.015***	0.0113
Bin 26			0.752***	0.0590	0.982***	0.0114
Bin 27			0.668***	0.0591	0.990***	0.0121
Bin 28			0.606***	0.0590	1.002***	0.0127
Bin 29			0.481***	0.0589	0.894***	0.0144
Bin 30			0.374***	0.0597	0.819***	0.0173
Bin 31			0.380***	0.0600	0.959***	0.0244
Bin 32			0.420***	0.0659	0.968***	0.0428
Bin 33					0.543***	0.0730
WSP_{mean}	-0.302***	0.00718			-0.827***	0.00769
WSP_{min}	-0.203***	0.00627			0.157***	0.00602
WSP_{max}	0.101***	0.00323			0.00297	0.00308
Observations	867,878		867,878		867,878	
F-Stat	14610		874.3		3934	
Prob > F	0		0		0	
Degree of Freedom	867875		867848		867845	

*** p<0.01, ** p<0.05, * p<0.1

h) Further results on car usage

Figure A.8: Average hourly speed: weekdays, weekends and PCAA days



Note: Figure shows the average hour-of-day difference speed between PCAA, weekdays and weekends. Seasonal fixed effects and weather controls are used. Sample is restricted from April 4th, 2016 to Dec 31st, 2019. Traffic data was obtained 343 sensors and video-detectors, mapped in Figure **??**.