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Wood-Burning Restrictions and Indoor Air Pollution: The Case of Air Quality Warnings in Southern Chile

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Wood-Burning Restrictions and Indoor Air Pollution: The Case of Air Quality Warnings in Southern Chile.*

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Abstract

Despite the extensive evidence linking particulate matter exposure to adverse health effects, a significant portion of the global population, especially in low-income countries, continues to depend on highly polluting fuels like wood-burning for cooking and heating. This study evaluates the immediate effects of wood-burning restrictions, triggered by air quality warnings, on levels of fine and coarse particulate matter in the city of Los Angeles, Chile. Employing a regression discontinuity design, we derive plausible causal estimates indicating that wood-burning restrictions significantly reduce daily concentrations of PM_{10} and $PM_{2.5}$ during the most severe air quality warning. A battery of additional estimations supports these findings. However, our empirical analysis suggests that, while effective, wood-burning restrictions may not be sufficient to lower air pollution concentrations to levels deemed safe for health.

JEL codes: Q53, Q56, Q40, I15, I25
Keywords: Wood combustion, wood burning, cooking fuels, indoor air pollution, air quality warnings, environmental alerts, Chile.

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1 Introduction

Residential heating through wood combustion constitutes a significant contributor to indoor air pollution, particularly in the global south (Duflo et al., 2008). Wood-burning predominantly releases particulate matter (Samburova et al., 2016), a pollutant associated with various adverse health effects (Ezzati and Kammen, 2002b), including premature mortality (Huang et al., 2018), lung cancer (Lepeule et al., 2018), and respiratory and cardiovascular diseases (Kim et al., 2017), in addition to several other adverse impacts on the general economic well-being of households in developing countries (Duflo et al., 2008). The degradation of air quality resulting from the combustion of this fuel can occur in both rural and urban areas (Hellén et al., 2008), with a more pronounced impact in cold regions. This is evident in the southern region of Chile (Jorquera et al., 2018; Schueftan et al., 2016), where cultural preferences shaped by resource availability have led to widespread use of wood-burning for heating and cooking (Schueftan et al., 2016), causing a decline in air quality in most urban areas. A striking example is the city of Los Ángeles, where wood-burning contributes to 96% and 86% of emissions of fine particulate matter ($PM_{2.5}$) and coarse particulate matter (PM_{10}), respectively. Consequently, Los Ángeles ranks as one of the most polluted cities in South America.

In this study, we assess the efficacy of a command-and-control policy implemented to manage atmospheric pollution during periods of poor air quality in the city of Los Ángeles. Since 2018, the Critical Episode Management Program (PGEC) has been designed to address air pollution by implementing both preventive and mitigative measures triggered by air quality warnings when pollution levels reach critical thresholds. Utilizing a three-tier system comprising *alerts*, *pre-emergencies*, and *emergencies*, these air quality warnings prompt various pollution control measures, including restrictions on wood-burning. Specifically, during *pre-emergencies*, household wood combustion is prohibited during afternoon hours on days with an issued warning, while *emergencies* extend this prohibition to the entire day. No mitigation measures are activated during *alerts*.

We particularly focus on the impact of these warnings (hereafter also called environmental episodes, or simply episodes) on concentrations of fine and coarse particulate matter (PM_{10} and $PM_{2.5}$, respectively). To identify effects, we use a sharp regression discontinuity (RD) design that compares pollution concentrations before and after the occurrence of an episode. We carry out our empirical estimation using daily and hourly concentrations of particulate matter from 2018 to 2022 obtained from monitoring stations that are located the area subject to restrictions. We complement this analysis with a battery of additional estimations, including a differences-in-differences (DID) estimation using pollution records from a nearby city and unaffected by the policy.

The results demonstrate that prohibiting the burning of wood leads to a reduction in particulate matter concentrations, but only during the strongest air quality warnings. Specifically, using a linear polynomial fit, we find daily pollution reductions of 34.7% and 34.9% for PM_{10} and $PM_{2.5}$ respectively during an environmental *emergency*, while no reductions are found for *pre-emergencies*. These results remain consistent when using an hourly approach. In particular, we find that air quality emergencies reduce 40% and 27% of hourly PM_{10} and $PM_{2.5}$ concentrations, respectively. When exploring heterogeneous effects by hours of the day, the results show that these reductions concentrate mostly at night when it is colder and the use of wood-burning heaters is likely higher. We consider these findings as strong evidence of the effectiveness of the strongest air quality warning. However, while the program exhibits some effectiveness, it is important to consider the persistently high average pollution levels in the city. It appears that prohibitions embedded in the mildest episode are insufficient to have a meaningful impact on pollution concentrations.

Our paper makes a significant contribution to the assessment of environmental policy programs designed to mitigate pollution, particularly indoor air pollution. Several studies evaluate policy interventions aimed at enhancing indoor air quality, including initiatives that involve subsidizing cleaner fuels (e.g., Brook and Smith (2000); Zhang et al. (2019)) or upgrading cooking technologies (Ezzati and Kammen, 2002a; Levine et al., 2018). While these interventions have demonstrated potential in enhancing air quality, recent scrutiny has been directed towards their cost-effectiveness and long-term adoption (Jeuland and Pattanayak, 2012; Bonan et al., 2017; Zhang et al., 2019). Factors such as liquidity constraints, information disparities, and cultural factors have emerged as potential impediments to the sustained implementation and acceptance of these strategies. These challenges underscore the significance of adopting a complementary approach in designing air quality improvement policies, particularly in addressing indoor air pollution in developing nations. Our study offers a potential solution to this complementarity issue by suggesting a policy mandate to curtail the use of residential heating during days of critical air pollution. To the best of our knowledge, our work represents the first attempt to evaluate such a policy, providing valuable insights into its feasibility and potential impact.

Our work also adds to the broad set of papers evaluating environmental policy targeting air pollution in Chile (e.g., Troncoso et al. (2012); Mullins and Bharadwaj (2015); Rivera (2021)), particularly those focused on indoor air pollution (Schueftan and González, 2015; Mardones and Cornejo, 2020). Our study aligns closely with Mardones and Cornejo (2020), which evaluates a similar policy in a southern city in Chile. However, we focus exclusively on causal identification, alongside considering heterogeneity in the various impacts that environmental episodes may entail. This methodological approach allows for a more nuanced understanding of the effectiveness and implications of environmental policy interventions.

The remainder of this document is organized as follows. In Section 2 we describe the air quality situation of Los Angeles. We present the data in Section 3 and the details of the empirical strategy in Section 4. Results are presented in Section 5, along with robustness analysis in Section 6. We conclude our analysis in Section 7.

2 Background

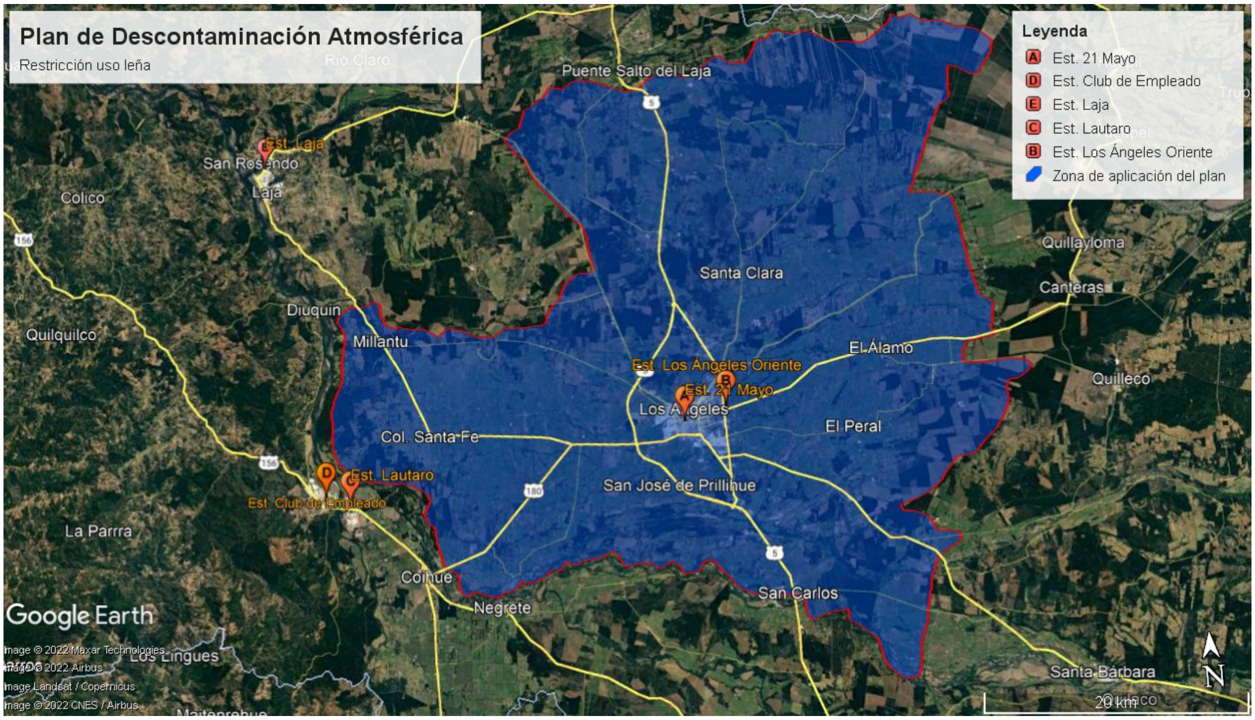
The city of Los Ángeles is situated approximately 514 kilometers south of Santiago, the capital of Chile. The primary source of air pollution emissions in this city is residential wood combustion, used mostly for household heating and cooking. It is estimated that over 87% of urban households in Los Ángeles rely on wood as their primary energy source for these activities, contributing to more than 80% of particulate matter pollution concentrations within the city.

In 2015, Los Ángeles was identified as one of the most polluted cities in the country, with daily concentrations of $PM_{2.5}$ and PM_{10} exceeding $150\mu g/m^3$ and $50\mu g/m^3$, respectively. Consequently, the Atmospheric Decontamination Plan (ADP) was formulated to enhance environmental quality standards within the city over a decade (Ministerio del Medio Ambiente, 2019). This plan entailed a series of structural measures for pollution control spanning short, medium, and long-term durations. Figure 1 depicts the spatial polygon over which these measures are in place.

This study focuses on a key short-term component of the ADP known as the Critical Episodes Management Program (PGEC). The PGEC consists of the issuance of 24-hour environmental episodes, or warnings, aimed at mitigating particulate matter concentrations during periods of critical air pollution, particularly during the winter season (from April 1 to September 30). More specifically, a comprehensive suite of preventive and mitigation measures is activated whenever pollution levels for $PM_{2.5}$ and PM_{10} reach critical thresholds. In these cases, a three-tier system of environmental warnings is activated (*Alerts*, *Pre-emergencies*, and *Emergencies*) which consequently trigger a series of restrictions on the use of wood-burning devices (SEREMI del Medio Ambiente, 2020). Table 1 shows in detail this system and the corresponding pollution thresholds for each of the episodes.

During the mildest episode, *Alerts*, no prohibitions are in place. Instead, authorities issue

Figure 1: Wood-Burning Restriction Polygon for Los Ángeles



Notes: This figure shows the wood-burning restriction polygon for Los Ángeles and the monitoring stations. Data obtained from Exempt Resolution No. 130 of the Regional Ministry of the Environment of the Bío Bío Region.

Table 1: Environmental Episodes and Pollution Levels

Air Quality Conditions	**Pollution Concentrations** $\mathbf{PM_{10}(\mu g/m^3)}$	$\mathbf{PM_{2.5}(\mu g/m^3)}$
Good	0 - 149	0 - 50
Regular	150 - 194	51 -79
Alert	195 -239	80 -109
Pre-emergency	240 - 329	110 - 169
Emergency	$\geq$ 330	$\geq$ 170

Notes: This table presents the different air quality levels as defined by the Ministry of the Environment, their equivalent daily average concentrations of fine particulate matter ($PM_{2.5}$) and coarse particulate matter (PM_{10}), and policy recommendations for the population included in the Primary Environmental Quality Standard for these pollutants. Particulate matter is measured in micrograms per cubic meter. Data obtained from the Ministry of the Environment.

recommendations and advocate for responsible and efficient heating practices. However, should daily pollution concentrations exceed $110\mu g/m^3$ for PM2.5 and $240\mu g/m^3$ for PM10, a *Pre-emergency* status is declared. This mandates the prohibition of wood-burning heaters, stoves, and boilers emitting more than $30\mu\text{g/m}^3$ of PM from 6 pm to midnight, along with traditional ovens throughout the entire day. In instances where daily concentrations surpass $170\mu g/m^3$ for PM2.5 and $330\mu g/m^3$ for PM10, an *Emergency* is declared and the ban on wood-burning heaters, stoves, and boilers is extended to 24 hours a day.

A comprehensive framework overseen by the Ministry of Health and the Ministry of the

Environment coordinates various actions to monitor the system of environmental episodes. These oversight strategies include monitoring the usage of open hearth fireplaces, regulating burning activities in wood-burning heaters and stoves, supervising the use of wood-burning heaters in commercial establishments and governmental bodies, and regulating their usage in apartment buildings, among others. Since 2021, authorities have monitored approximately 24,956 homes, conducting detailed inspections on 402 of them and initiating investigations on 139 units. Non-compliant households risk fines ranging from 63,000 pesos (equivalent to 65 USD) to approximately one million two hundred thousand pesos (equivalent to 1,300 USD). Despite these efforts, concerns have been raised by the highest municipal authority regarding the effectiveness of this plan, indicating a need for empirical evaluation of the functioning of this command-and-control policy.[1]

3 Data

We collect daily and hourly concentrations of $PM_{2.5}$ and PM_{10}, as well as meteorological data (wind speed, temperature, humidity), from two air quality monitoring stations within the MACAM-2 network of the National Air Quality Information System (SINCA) spanning the years 2018 to 2022. Additionally, information regarding days with wood-burning bans and forecasts for each environmental episode is obtained from the Regional Ministry of the Environment (SEREMI) of the Bío Bío Region. Table 2 presents the total number of episodes issued each year during the study period.

Table 2: Environmental Episodes Triggering Wood-Burning Bans Issued Every Year

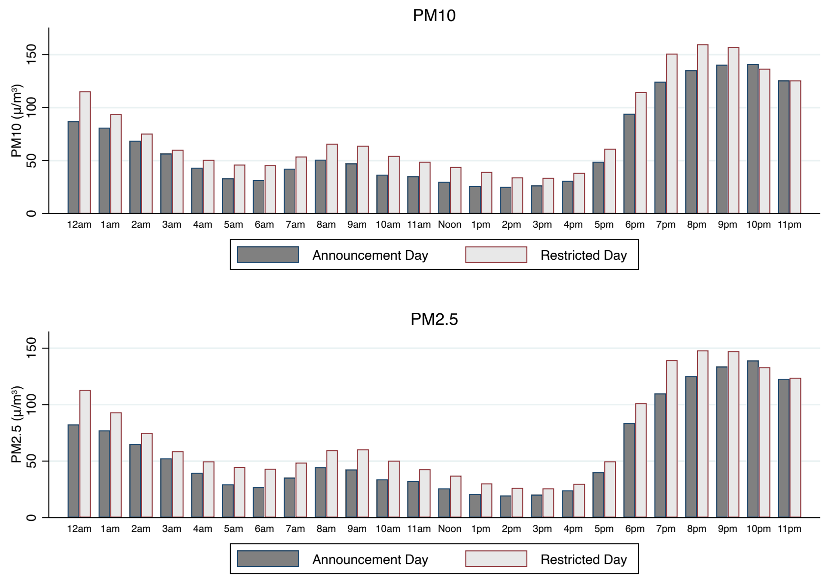
Year	Pre-emergency	Emergency	Total
2018	35	12	47
2019	14	2	16
2020	20	1	21
2021	13	3	16
2022	18	1	19
Total	100	19	119

Notes: This table shows the total number of days of Pre-emergencies and Emergencies declared from 2018 to 2022 in the city of Los Ángeles. Data obtained from the Regional Ministry of the Environment of the Bío Bío Region.

Figures 2 and 3 depict the hourly profiles of both PM_{10} and $PM_{2.5}$ concentrations during days marked by *Pre-emergencies* and *Emergencies*, respectively. Additionally, alongside plotting the day of the episode, which corresponds to the day when wood-burning restrictions are in place, we include average concentrations during the day preceding the episode that

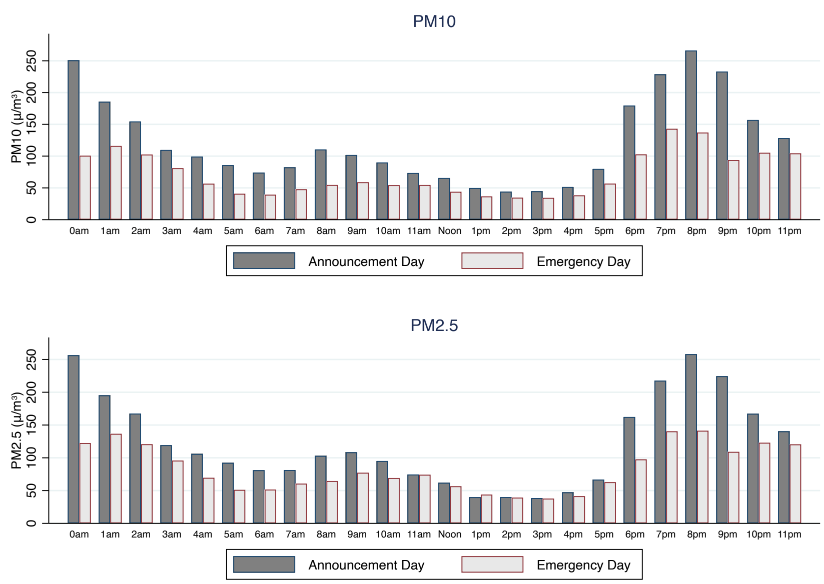
[1] See for instance: https://www.latribuna.cl/noticias/2021/06/30/krause-el-plan-de-descontaminacion-en-los-angeles-hay-que-revisarlo.html.

Figure 2: Hourly PM_{10} and $PM_{2,5}$ Concentrations During *Pre-emergencies*



Notes: This figure shows hourly average concentrations of PM_{10} (top panel) and $PM_{2.5}$ (bottom panel) during *Pre-emergency* days and the day of the announcement (day before) from 2018 to 2022. Particulate matter is measured in micrograms per cubic meter ($\mu g/m^3$). Data obtained from SINCA.

Figure 3: Hourly PM_{10} and $PM_{2,5}$ Concentrations During *Emergencies*



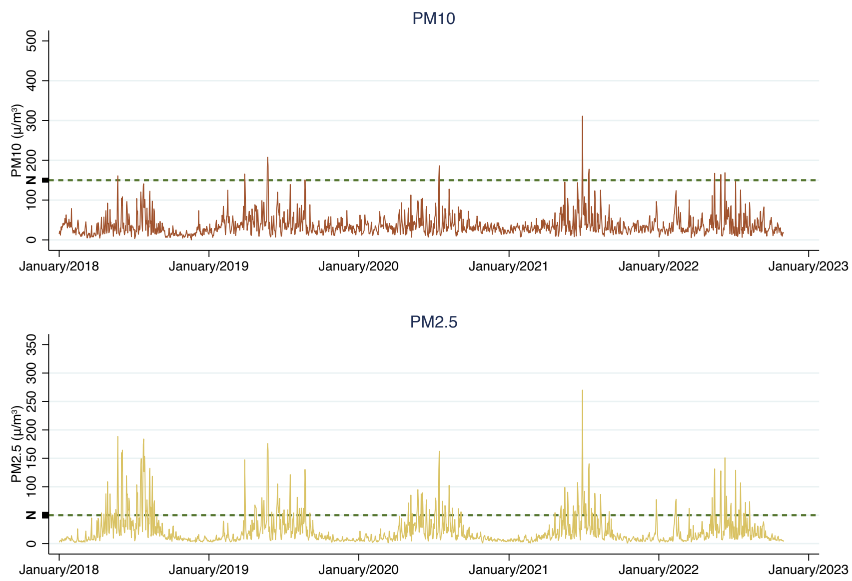
Notes: This figure shows hourly average concentrations of PM_{10} (top panel) and $PM_{2.5}$ (bottom panel) during *Emergency* days and the day of the announcement (day before) from 2018 to 2022. Particulate matter is measured in micrograms per cubic meter ($\mu g/m^3$). Data obtained from SINCA.

corresponds to the day when the announcement is made. The first thing to notice is that, as anticipated, pollution concentrations are higher during days characterized by an *Emergency*.

Furthermore, there is an evident hourly cycle in both depictions, indicating elevated pollution concentrations during nighttime, particularly after 6 pm, with peak values occurring between 8 pm and midnight—a timeframe coinciding with when most household members are indoors.

Moreover, we see that pollution levels on days preceding a *Pre-emergency* are generally lower than during the actual *Pre-emergency* day, across almost all hours. Conversely, in the days leading up to an *Emergency*, concentrations are notably higher throughout almost all hours compared to the day of the *Emergency* itself. This suggests that air pollution concentrations may be mitigated during this strongest episode.

Figure 4: Daily PM_{10} and $PM_{2,5}$ Concentrations Over Time



Notes: This figure shows the daily average concentrations of PM_{10} and $PM_{2.5}$ in Los Ángeles from 2018 to 2022. The green dotted line represents Chile's standard for each pollutant. Particulate matter is measured in micrograms per cubic meter ($\mu g/m^3$). Data obtained from SINCA.

Figure 4 illustrates daily particulate matter concentrations in Los Ángeles from 2018 to 2022. The figure reveals a marked seasonality with higher concentrations occurring during the fall and winter months, a pattern that can be attributed to two primary factors. Firstly, the presence of meteorological conditions (e.g., poor ventilation, low temperatures, thermal inversion, high pressure) during the fall and winter impede the dispersion of pollutants. Secondly, an increase in particulate matter emissions in the city, primarily stemming from the use of wood for heating, which intensifies during the colder months between April and September.

The figure also highlights that, during certain periods, daily PM_{10} concentrations (top panel) exceed not only the World Health Organization (WHO) recommended norm of 50

μg/m^3 for a 24-hour average but also the local standard of 150 μg/m^3 for a 24-hour average, which is already relatively high. This is even more concerning and frequent for $PM_{2.5}$ concentrations (bottom panel), underscoring the significant health risk posed by pollution levels in this city to the population.

Descriptive statistics on average pollution concentrations are presented in Table 3 for all days in the analysis, days with episodes, and days preceding an episode. Similar statistics are present for weather variables in Appendix Table A1. Consistent with the pattern observed in Figure 3, the data in Table 3 reveals that average concentrations of both pollutants decrease during days with an Emergency compared to pollution concentrations reached the day before. However, this differs from average levels during Pre-emergencies. This observation suggests that the program may yield results that align only with the most stringent wood-burning restrictions.

Table 3: Descriptive Statistics of Hourly PM_{10} and $PM_{2.5}$ Concentrations

Variable	N	Mean	Std. Dev.	Min	Max
Panel A: Full Sample					
PM_{10}	84,253	36.52	53.52	0	1,394
$PM_{2.5}$	84,253	22.01	47.17	0	1,383
Panel B: Days Before *Pre-emergencies*					
PM_{10}	4,800	72.80	124.04	0	1,384
$PM_{2.5}$	4,800	68.09	112.89	0	1,383
Panel C: Days with *Pre-emergencies*					
PM_{10}	4,800	77.97	119.34	0	1,394
$PM_{2.5}$	4,800	72.19	106.86	0	1,360
Panel D: Days Before *Emergencies*					
PM_{10}	912	110.76	153.51	0	1,124
$PM_{2.5}$	912	120.52	130.38	0	1,019
Panel E: Days with *Emergencies*					
PM_{10}	912	72.49	114.81	0	955
$PM_{2.5}$	912	83.71	100.45	0	908

Notes: This table shows descriptive statistics of the pollutants PM_{10}, $PM_{2.5}$, and meteorological variables on an hourly basis between 2018-2022. Panel A displays data for the entire period. Panels B and C present data for the variables during days before and during *Pre-emergencies*, respectively. Panels D and E show data for the variables during days before and during *Emergencies*, respectively. Particulate matter is measured in micrograms per cubic meter (μg/m^3). Data obtained from SINCA.

4 Methods

This study aims to assess the causal impact of wood-burning restrictions issued by air quality warnings (i.e., *Pre-Emergency* and *Emergency* episodes) on daily and hourly concentrations of particulate matter in the city of Los Ángeles, Chile. Due to the design of this policy, we apply a sharp regression discontinuity (RD) design that uses time as the running variable and the declaration of an environmental episode as the treatment variable. This treatment variable takes the value one if an episode is issued on a specific day, and zero otherwise. Our key identifying assumption here is that, in the absence of the treatment (an environmental episode), pollution concentrations should be similar around the threshold.

Let P_{it} represents average pollution concentrations (logged) in station i during time t, we specifically estimate variations of the following equation:

$$P_{it} = \beta_0 + \beta_1 Episode_t + \beta_2 f(x) + \beta_3 Episode_t f(x) + \lambda X_{it} + \delta_i + \mu_t + \varepsilon_{it}, \tag{1}$$

where $Episode_t$ is a binary variable that takes the value of 1 if day (hours) t is restricted, $x = [t - c]$ is the assignment indicating the number of days (hours) before and after an episode, and c represents the cut-off, or the day with an episode in place. We normalize the cut-off to 0, so negative and positive values for x represent days (hours) before and after an episode. Equation (1) also includes $f(x)$, a first-order polynomial function. The vector X_{it} is a set of control variables, including meteorological variables (temperature, wind speed, and relative humidity). The parameter δ_i represents a station-fixed effect, μ_t a time-fixed effect (year, month, day of the week, and hour of day), and ϵ_{it} the idiosyncratic term.

The parameter of interest in Equation (1) is β_1, which quantifies the disparity in pollution concentrations before and after an environmental episode. A negative and statistically significant β_1 provides evidence of the effectiveness of wood-restriction bans, as mandated by environmental episodes, in reducing average pollution concentrations. We estimate Equation (1) using an Ordinary Least-Squares (OLS) estimator, clustering standard errors at the station level. In a robustness analysis, we employ Newey-West standard errors to address potential serial correlation in the data.

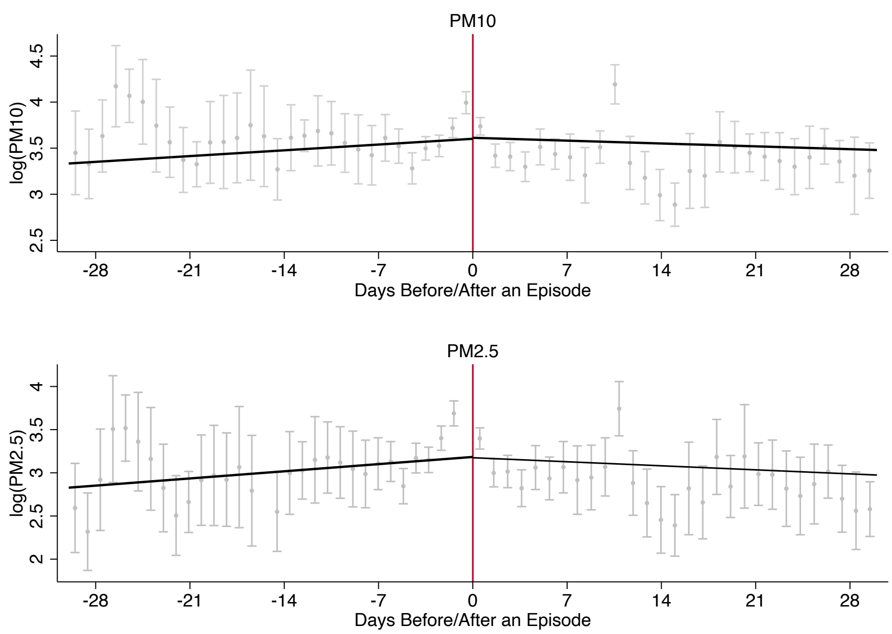
It is important to note that the choice of the functional form of the adjustment polynomial in the RD specifications is critical. By using an adjustment polynomial, we impose a specific structure on the relationship between the running variable x and the outcome variable P_{it}. If the actual relationship between these variables does not conform well to the chosen polynomial's functional form, the model may fail to accurately capture the true relationship, leading to biased estimates. In this spirit, we explore not only a first-order functional form but also a quadratic form to model $f(x)$.

5 The Effectiveness of Wood-Burning Bans on Pollution Concentrations

5.1 Daily Approach

We start with an examination of a data-driven approach that pool air quality warnings together. To this end, Figure 5 illustrates a regression discontinuity plot on daily concentrations of PM10 and PM2.5 utilizing a linear fit, with a bandwidth extending 30 days before and after an air quality warning. The vertical line represents the day with an environmental episode that triggers the restrictions on wood burning (i.e., the cut-off point). While there is a clear rise in air pollution levels in the days leading up to an episode followed by a subsequent decline in the levels of both pollutants, the disparity before and after fails to achieve statistical significance. This suggests that restrictions associated with both types of air quality warnings may not lead to a significant effect on enhancing air quality.

Figure 5: The Data-Driven Impact of Pooled Episodes on Daily Pollution Concentrations



Notes: This figure display the data-driven impact of air quality warnings on the (logged) daily average concentrations of particulate matter using a 30-day bandwidth before and after a warning. The top figure shows the results for PM_{10}, while the bottom figure shows the results for $PM_{2.5}$. Data obtained from SINCA for 2018 to 2022.

We present the results of estimating Equation (1) in Table 4 for a pooled approach, and in Tables 5 and 6 for air quality *pre-emergencies* and *emergencies*, respectively. The data-

Table 4: The Impact of Pooled Episodes on Daily Pollution Concentrations

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: PM_{10}						
1[Episode]	0.159	0.107	0.0134	0.0444	-0.0316	-0.181
	(0.401)	(0.457)	(0.0667)	(0.411)	(0.463)	(0.118)
N	1,405	1,405	1,405	1,405	1,405	1,405
Panel B: $PM_{2.5}$						
1[Episode]	0.152	0.0982	-0.0706	0.0482	0.0157	-0.213
	(0.667)	(0.722)	(0.0697)	(0.615)	(0.671)	(0.131)
N	1,413	1,413	1,413	1,413	1,413	1,413
Controls		✓	✓		✓	✓
Station fixed-effects			✓			✓
Time fixed-effects			✓			✓
Order polyn.	1	1	1	2	2	2
Statistics Panel A:						
Mean left	43.35	43.35	43.35	43.35	43.35	43.35
Mean right	37.46	37.46	37.46	37.46	37.46	37.46
Bandwidth	8.832	12.01	5.564	12.20	10.01	5.631
Statistics Panel B:						
Mean left	27.90	27.90	27.90	27.90	27.90	27.90
Mean right	19.53	19.53	19.53	19.53	19.53	19.53
Bandwidth	9.394	10.23	3.575	11.31	11.36	4.708

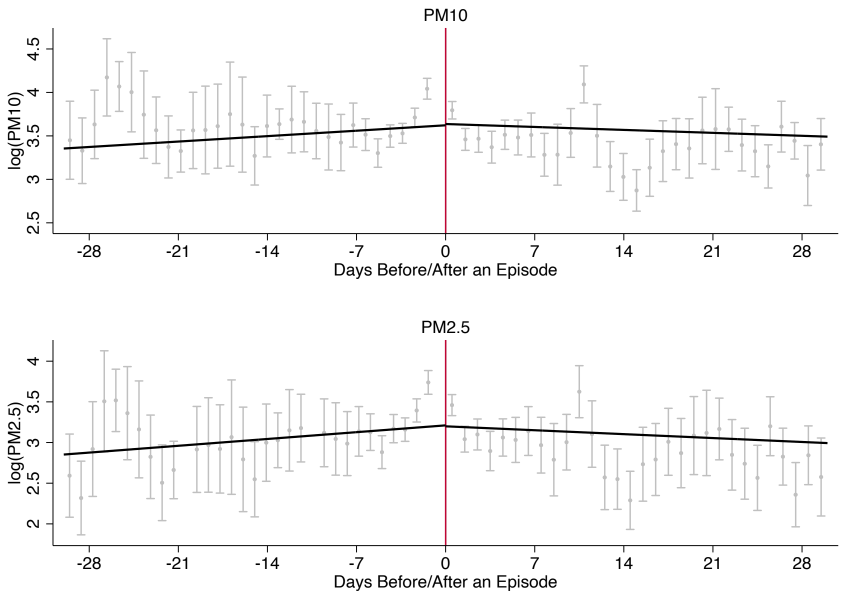
Notes: This table presents the impact of pooled air quality warnings on the (logged) daily average concentrations of particulate matter. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, and day of the week). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Clustered standard errors by station in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

driven plots for these two warnings are depicted in Figure 6.[2] We provide estimations for both a linear model (columns (1), (2), and (3)) and a quadratic polynomial fit (columns (4), (5), and (6)). Columns (1) and (4) display the RD impact without controls, while columns (2) and (5) incorporate controls. Additionally, columns (3) and (6) include a set of time and station fixed effects, representing our preferred specification. We maintain this structure in subsequent tables.

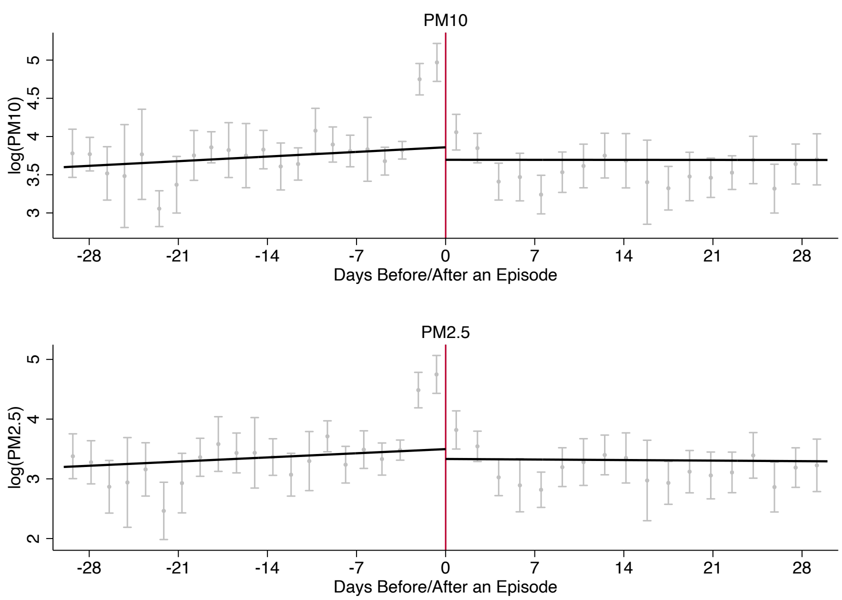
The results from pooling the episodes in Table 4 indicate that, on average, air quality warnings do not have a short-term impact on air pollution concentrations in Los Ángeles. However, a closer examination of each episode reveals heterogeneous effects. Specifically, while no effects are observed for air quality *pre-emergencies*, the results for *emergencies* in Table 6 demonstrate that these episodes effectively reduce air pollution concentrations. Employing our preferred specification with a linear fit, Table 6 shows that, on average,

[2] We conduct a series of tests to validate the RD approach, particularly examining the continuity of control variables. Graphs illustrating these tests are available upon request.

Figure 6: The Data-Driven Impact of Pre-emergencies and Emergencies on Daily Pollution Concentrations



(a) Air Quality Pre-emergencies



(b) Air Quality Emergencies

Notes: This figure display the data-driven impact of air quality *pre-emergencies* and *emergencies* on the (logged) daily average concentrations of particulate matter using a 30-day bandwidth before and after a warning. The top figure shows the results for PM_{10}, while the bottom figure shows the results for $PM_{2.5}$. Data obtained from SINCA for 2018 to 2022.

air quality *emergencies* lead to a 40% reduction in daily PM10 concentrations and a 35% reduction in PM2.5. Similar effects, albeit more pronounced, are observed in column (6) with a second-order polynomial fit. The impact of environmental *emergencies*, as opposed to *pre-emergencies*, is evident when examining the data-driven analysis in Figure 6, particularly at the discontinuity of the strongest episode (panel B).

Table 5: The Impact of Pre-emergencies on Daily Pollution Concentrations

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: PM_{10}						
1[Pre-emergency]	0.158	0.107	0.00988	0.0643	-0.00470	-0.152
	(0.391)	(0.450)	(0.0539)	(0.401)	(0.454)	(0.110)
N	1,379	1,379	1,379	1,379	1,379	1,379
Panel B: $PM_{2.5}$						
1[Pre-emergency]	0.160	0.0723	-0.0597	0.0612	0.0282	-0.150
	(0.658)	(0.735)	(0.0670)	(0.604)	(0.671)	(0.129)
N	1,387	1,387	1,387	1,387	1,387	1,387
Controls		✓	✓		✓	✓
Station fixed-effects			✓			✓
Time fixed-effects			✓			✓
Order polyn.	1	1	1	2	2	2
Statistics Panel A:						
Mean left	42.91	42.91	42.91	42.91	42.91	42.91
Mean right	36.87	36.87	36.87	36.87	36.87	36.87
Bandwidth	8.756	15.28	5.344	12.22	10.77	6.090
Statistics Panel A:						
Mean left	27.52	27.52	27.52	27.52	27.52	27.52
Mean right	18.89	18.89	18.89	18.89	18.89	18.89
Bandwidth	9.348	14.53	3.643	8.957	11.91	5.084

Notes: This table presents the impact of air quality *pre-emergencies* on the (logged) daily average concentrations of particulate matter. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, and day of the week). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Clustered standard errors by station in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Next, we delve into the evolution of the policy since its implementation by examining its heterogeneous impact by year. Table A2 illustrates the policy's progression over the years, presenting the heterogeneous effects for all combined episodes and separately for pre-emergencies and emergencies.

Similar to Table 6, the results underscore the effectiveness of emergency episodes alone. Specifically, a notable reduction, significant at the 10% level, is observed, with a decrease of 37.5% for PM_{10} and 35.5% for $PM_{2.5}$ in 2019 compared to 2018, the program's initiation year. During 2020 and 2021, no discernible effect of the restrictions is evident, consistent

Table 6: The Impact of Emergencies on Daily Pollution Concentrations

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: PM_{10}						
1[Emergency]	-0.744*	-0.0182	-0.412***	-0.746	-0.466	-0.503***
	(0.393)	(0.465)	(0.0521)	(0.486)	(0.426)	(0.0585)
N	626	626	626	626	626	626
Panel B: $PM_{2.5}$						
1[Emergency]	-0.643	0.103	-0.346***	-0.942	-0.462	-0.518***
	(0.612)	(0.710)	(0.0819)	(0.625)	(0.564)	(0.171)
N	629	629	629	629	629	629
Controls		✓	✓		✓	✓
Station fixed-effects			✓			✓
Time fixed-effects			✓			✓
Order polyn.	1	1	1	2	2	2
Statistics Panel A:						
Mean left	47.61	47.61	47.61	47.61	47.61	47.61
Mean right	33.59	33.59	33.59	33.59	33.59	33.59
Bandwidth	5.275	7.248	4.215	12.46	10.70	8.003
Statistics Panel B:						
Mean left	32.34	32.34	32.34	32.34	32.34	32.34
Mean right	15.88	15.88	15.88	15.88	15.88	15.88
Bandwidth	6.375	9.583	5.822	11.85	11.16	8.101

Notes: This table presents the impact of air quality *emergencies* on the (logged) daily average concentrations of particulate matter. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, and day of the week). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Clustered standard errors by station in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

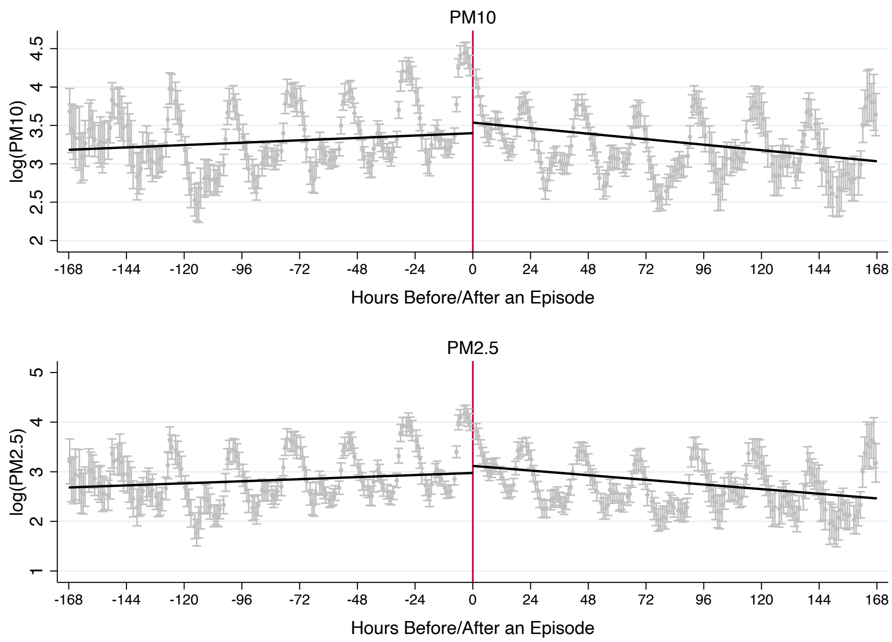
with pandemic-related lockdowns that compelled people to stay in their homes for extended periods, likely increasing heating usage. Finally, in 2022, a statistically significant reduction of 38.8% for PM_{10} and 69.1% for $PM_{2.5}$ is observed.

5.2 Hourly Approach

In this section, we complement the previous approach with an hourly analysis. Figure 7 displays the adjustment of hourly concentrations of PM10 and PM2.5, seven days before and after an episode, regardless of its type. As observed, there is no clear decrease observed in the levels of both pollutants, suggesting that the restrictions may not have an effect on improving air quality. A parametric analysis corroborates this result, which is also consistent with the daily specification (see Table 7).

More interesting is the examination of heterogeneous effects by type of episode. We present the data-driven results of this analysis in Figure 8 for *pre-emergencies* (panel (a)) and *emergencies* (panel (b)), and the parametric analysis in Tables 8 and 9 for air quality *pre-emergencies* and *emergencies*, respectively.

Figure 7: The Data-Driven Impact of Pooled Episodes on Hourly Pollution Concentrations



Notes: This figure display the data-driven impact of air quality warnings on the (logged) hourly average concentrations of particulate matter using a 7-day bandwidth before and after a warning. The top figure shows the results for PM_{10}, while the bottom figure shows the results for $PM_{2.5}$. Data obtained from SINCA for 2018 to 2022.

Once again, the results indicate that the mildest episode, *pre-emergencies*, has no effect on air pollution concentrations. Wood-burning restrictions imposed by this air quality warning appear to be insufficient to curtail pollution concentrations during these critical days. However, consistent with the daily analysis, air quality *emergencies* effectively reduce air pollution concentrations. The results of a linear fit in Table 9 show that this strongest episode leads to a 40% reduction in hourly PM_{10} concentrations and a 27% reduction in hourly $PM_{2.5}$ concentrations. The impact of this air quality warning is also evident in the bottom panel of Figure 8.

5.3 Heterogeneous Effects by Hours of the Day

The preceding findings consistently demonstrate the effectiveness of air quality *emergencies* in reducing air pollution levels during days of critical air contamination, regardless of whether we adopt a daily or hourly approach. However, one may question during which hours of the day these reductions are most significant. If households primarily burn wood during specific

Table 7: The Impact of Pooled Episodes on Hourly Pollution Concentrations

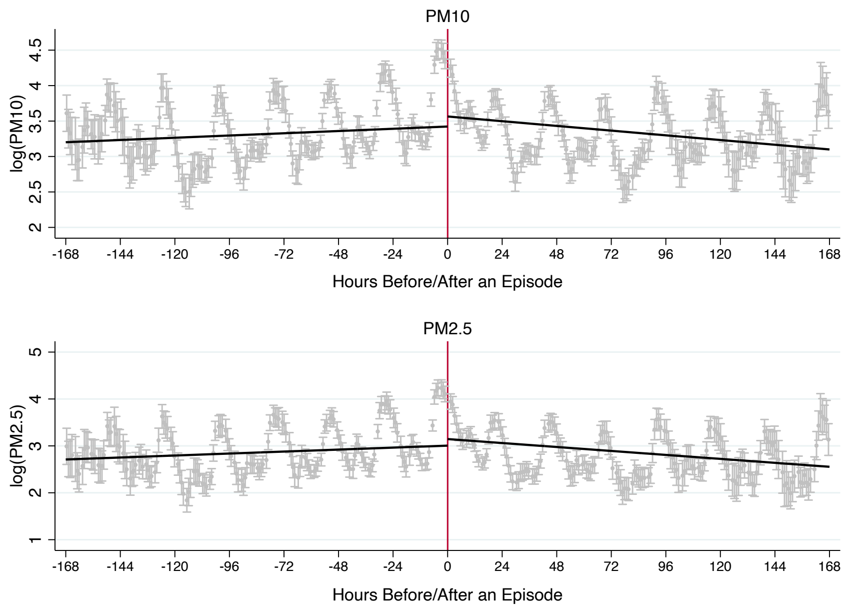
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: PM_{10}						
1[Episode]	0.0820	0.00365	0.153	-0.252	-0.252	0.147
	(0.351)	(0.372)	(0.120)	(0.489)	(0.511)	(0.189)
N	22,210	22,210	22,210	22,210	22,210	22,210
Panel B: $PM_{2.5}$						
1[Episode]	0.117	-0.104	0.209	-0.265	-0.256	0.184
	(0.592)	(0.658)	(0.132)	(0.704)	(0.743)	(0.157)
N	22,210	22,210	22,210	22,210	22,210	22,210
Controls		✓	✓		✓	✓
Station fixed-effects			✓			✓
Time fixed-effects			✓			✓
Order polyn.	1	1	1	2	2	2
Statistics Panel A:						
Mean left	49.58	49.58	49.58	49.58	49.58	49.58
Mean right	38.82	38.82	38.82	38.82	38.82	38.82
Bandwidth	40.72	69.82	43.80	50.22	59.35	72.67
Statistics Panel B:						
Mean left	37.93	37.93	37.93	37.93	37.93	37.93
Mean right	19.64	19.64	19.64	19.64	19.64	19.64
Bandwidth	41.78	47.19	37.50	49.26	60.66	80.27

Notes: This table presents the impact of pooled air quality warnings on the (logged) hourly average concentrations of particulate matter. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, day of the week, and hour of the day). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Clustered standard errors by station in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

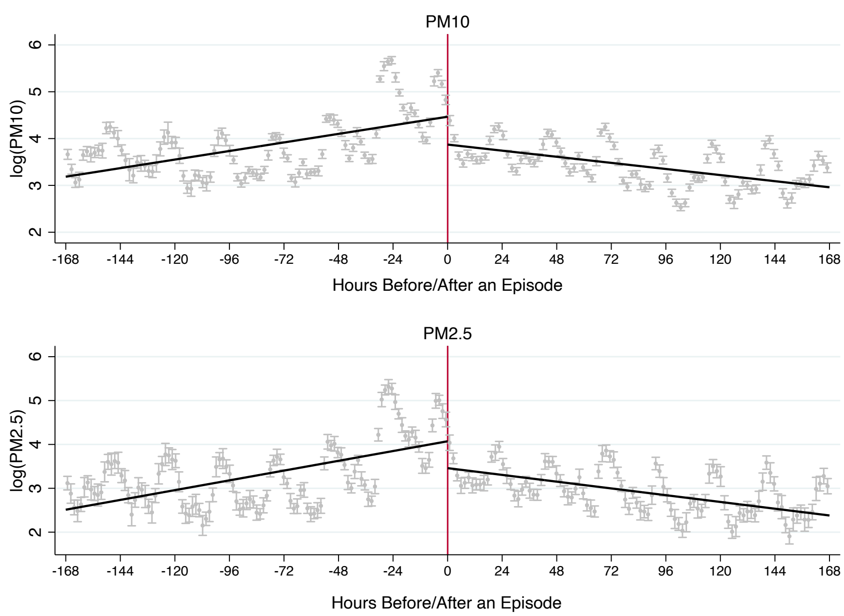
hours, such as nighttime for cooking dinner or warming the house, then we would expect the statistically significant effects to predominantly occur during nighttime hours. We present these results in Appendix Table A3 for both a pooled analysis and for each type of episode, using blocks of 3 hours, with the 3-6 pm block (the block right before the imposed restrictions) as the baseline.

The findings in Appendix Table A3 indicate that the previously estimated reductions in air pollution primarily occur during nighttime hours, specifically after 6 pm. Interestingly, this new flexible estimation strategy now reveals statistically significant effects not only for air quality *emergencies* but also for *pre-emergencies*. However, for *emergencies*, we lose statistical significance in the case of $PM_{2.5}$ for the blocks between 6 pm and midnight. Nevertheless, meaningful reductions are observed late at night and early in the morning, between midnight and 9 am. These effects align with the difference in persistence of these two pollutants in the atmosphere, as fine particulate matter tends to linger longer in the air,

Figure 8: The Data-Driven Impact of Pre-emergencies and Emergencies on Hourly Pollution Concentrations



(a) Air Quality Pre-emergencies



(b) Air Quality Emergencies

Notes: This figure display the data-driven impact of air quality *pre-emergencies* and *emergencies* on the (logged) hourly average concentrations of particulate matter using a 7-day bandwidth before and after a warning. The top figure shows the results for PM_{10}, while the bottom figure shows the results for $PM_{2.5}$. Data obtained from SINCA for 2018 to 2022.

Table 8: The Impact of Pre-emergencies on Hourly Pollution Concentrations

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: PM_{10}						
1[Pre-emergency]	0.0969	0.0601	0.152	-0.280	-0.268	0.161
	(0.355)	(0.355)	(0.118)	(0.499)	(0.514)	(0.211)
N	21,559	21,559	21,559	21,559	21,559	21,559
Panel B: $PM_{2.5}$						
1[Pre-emergency]	0.0649	0.0659	0.164	-0.340	-0.274	0.214
	(0.592)	(0.623)	(0.102)	(0.722)	(0.748)	(0.203)
N	21,559	21,559	21,559	21,559	21,559	21,559
Controls		✓	✓		✓	✓
Station fixed-effects			✓			✓
Time fixed-effects			✓			✓
Order polyn.	1	1	1	2	2	2
Statistics Panel A:						
Mean left	48.88	48.88	48.88	48.88	48.88	48.88
Mean right	38.28	38.28	38.28	38.28	38.28	38.28
Bandwidth	36.92	80.70	45.37	48.96	56.45	62.36
Statistics Panel B:						
Mean left	37.34	37.34	37.34	37.34	37.34	37.34
Mean right	19.04	19.04	19.04	19.04	19.04	19.04
Bandwidth	46.17	56.59	49.03	46.53	57.14	60.36

Notes: This table presents the impact of air quality *pre-emergencies* on the (logged) hourly average concentrations of particulate matter. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, day of the week, and hour of the day). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Clustered standard errors by station in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

requiring more time for these particles to dissipate.

5.4 Long-Lasting Effects

Building on the preceding findings, we investigate whether the policy's effects persist beyond the immediate aftermath of the episodes. As previously noted, one notable characteristic of these pollutants is their capacity to linger in the atmosphere, potentially exerting a lasting impact over successive days. In this context, there is a possibility that the positive effects of certain warnings may extend beyond the initial 24-hour period.

With this consideration in mind, Appendix Table A4 presents the results for our preferred daily specification using 1-day lead pollution concentrations (i.e., pollution measured one day forward). As depicted, the outcomes for the pooled analysis and for *pre-emergencies* alone indicate no significant effect on either pollutant, consistent with earlier findings. In

Table 9: The Impact of Emergencies on Hourly Pollution Concentrations

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: PM_{10}						
1[Emergency]	-0.577**	-0.802***	-0.403***	-0.563**	-0.545***	-0.400**
	(0.232)	(0.310)	(0.146)	(0.241)	(0.209)	(0.203)
N	6,333	6,333	6,333	6,333	6,333	6,333
Panel B: $PM_{2.5}$						
1[Emergency]	-0.979*	-0.788*	-0.265***	-0.730*	-0.507	-0.123
	(0.550)	(0.472)	(0.0761)	(0.436)	(0.431)	(0.117)
N	6,333	6,333	6,333	6,333	6,333	6,333
Controls		✓	✓		✓	✓
Station fixed-effects			✓			✓
Time fixed-effects			✓			✓
Order polyn.	1	1	1	2	2	2
Statistics Panel A:						
Mean left	71.39	71.39	71.39	71.39	71.39	71.39
Mean right	38.18	38.18	38.18	38.18	38.18	38.18
Bandwidth	24.93	15.69	9.025	50.91	69.05	23.82
Statistics Panel B:						
Mean left	56.70	56.70	56.70	56.70	56.70	56.70
Mean right	19.88	19.88	19.88	19.88	19.88	19.88
Bandwidth	16.98	21.27	15.28	57.92	51.73	31.00

Notes: This table presents the impact of air quality *emergencies* on the (logged) hourly average concentrations of particulate matter. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, day of the week, and hour of the day). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Clustered standard errors by station in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

contrast, a notable reduction at the 1% significance level is evident for both PM_{10} and $PM_{2.5}$, with reductions of 46.3% and 44.4%, respectively. This suggests a sustained decrease in particulate matter attributable to restrictions during air quality *emergencies*. Such an extended impact represents a health advantage for the population, highlighting a substantial decrease in both pollutants over an extended period.

6 Robustness Checks

6.1 Monitoring Stations Outside the Restricted Area

As previously depicted in Figure 1, Los Angeles is located substantially close to Nacimiento, a city situated 30 kilometers southwest. Despite this proximity, Nacimiento is not subject to the wood-burning restrictions during days of critical air pollution. This situation provides us with the opportunity to employ pollution records in Nacimiento as a falsification test. Since the city is unaffected by the policy under analysis, we should not observe any significant impact of these warnings on its pollution records. Therefore, we examine the impact of these warnings on Nacimiento's daily pollution records using a combination of pooled episodes, *Pre-emergencies*, and *Emergencies*. The results of this analysis are presented in Table 10.

As expected, the policy yields no discernible effect on Nacimiento's pollution records, even during the strongest episodes. Considering that Nacimiento is relatively close to Los Angeles and it likely experiences similar weather conditions, a null impact of the policy under analysis on Nacimiento's pollution concentrations provides compelling evidence of the effectiveness of this policy in the city of Los Angeles.

Table 10: Impact of Episodes on Daily Pollution Concentrations of an Unaffected City

	Episodes		Pre-emergencies		Emergencies	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: PM_{10}						
1[Episode]	0.00588	0.0253	0.00925	0.113	-0.280	-0.410
	(0.0743)	(0.0925)	(0.0814)	(0.0843)	(0.206)	(0.280)
N	1,022	1,022	1,011	1,011	498	498
Panel B: $PM_{2.5}$						
1[Episode]	-0.0233	-0.00196	-0.0186	0.0447	-0.200	-0.345
	(0.0709)	(0.0844)	(0.0731)	(0.0786)	(0.240)	(0.287)
N	1,021	1,021	1,010	1,010	497	497
Controls	✓	✓	✓	✓	✓	✓
Station fixed-effects	✓	✓	✓	✓	✓	✓
Time fixed-effects	✓	✓	✓	✓	✓	✓
Order polyn.	1	2	1	2	1	2

Notes: This table shows the impact of air quality warnings on Nacimiento's (logged) daily average pollution concentrations. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. The regressions include weather controls (temperature, wind speed, humidity), and station and time fixed effects (year, month, and day of the week). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Clustered standard errors by station in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

6.2 Difference-In-Difference Estimation

The absence of policy impacts on pollution concentrations in Nacimiento allows us to use this city as a counterfactual in a difference-in-differences estimation. Assuming similar sociodemographic and climatic characteristics across these cities, and considering that Nacimiento is located upwind of Los Angeles, we can derive causal effects by simply comparing pollution records across the two cities before and after an environmental episode is issued. We estimate the following specification:

$$P_{it} = \gamma_0 + \gamma_1 1[Episode]_t + \gamma_2 1[Angeles]_i \times 1[Episode]_t + \lambda X_{it} + \delta_i + \mu_t + \eta_{it}, \quad (2)$$

where $1[Angeles]$ is an indicator that takes 1 if the pollution record i belongs to Los Angeles and 0 if it belongs to Nacimiento, δ_i is a station fixed-effect and η_{it} is an idiosyncratic error. Our parameter of interest here is γ_2, which represents the difference in pollution records between the two cities before and after an episode. Under the identifying assumption of parallel pollution trends in these two cities before the treatment, then γ_2 represents the causal effect of the policy under analysis. Appendix Figure A1 presents an overview of this common trends assumption depicting hourly average PM concentrations in the two cities 96 hours before an episode. As observed, the two trends follow a similar pattern.

The results of estimating Equation (2) are presented in Table 11 for both daily and hourly analyses. In both cases, the findings reveal an impact consistent with the baseline RD estimation. Specifically, the strongest air quality warning, an *Emergency*, effectively reduces air pollution concentrations stemming from wood-burning activities in the treated city.

Table 11: The Impact of Episodes on Pollution Concentrations Using an DID Estimator

	Daily Concentrations		Hourly Concentrations	
	PM_{10}	$PM_{2,5}$	PM_{10}	$PM_{2,5}$
Panel A: Pooled Episodes				
1[Angeles]× 1[Episodes]	-0.0233	0.0274	0.0272	0.0737
	(0.0895)	(0.0880)	(0.0871)	(0.0860)
N	436	436	10,159	10,154
Panel B: Heterogeneous Effects				
1[Angeles]× 1[Pre-emergencies]	-0.0558	0.00362	-0.0147	0.0388
	(0.0927)	(0.0908)	(0.0360)	(0.0374)
N	410	410	9,523	9,523
1[Angeles]× 1[Emergencies]	-0.375**	-0.304*	-0.260***	-0.314***
	(0.182)	(0.161)	(0.0610)	(0.0632)
N	50	50	1,182	1,179
Controls	✓	✓	✓	✓
Station fixed-effects	✓	✓	✓	✓
Time fixed-effects	✓	✓	✓	✓

Notes: This table shows the impact of air quality warnings on (logged) daily and hourly concentrations of PM_{10} and $PM_{2.5}$ in Los Ángeles using a DID estimator. Panel A shows the results of a pooled analysis. Panel B shows the results by type of episode. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, and day of the week). Clustered standard errors by station in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

6.3 Air Quality Alerts

As previously mentioned, air quality alerts are the mildest environmental episodes and, unlike pre-emergencies and emergencies, they do not impose wood-burning bans. Instead, they only provide health recommendations and encourage responsible use of heaters in households. Therefore, we should not expect a significant effect of this type of episode on air pollution concentrations.[3] We test this by estimating Equation (1) for this type of episode. The results, displayed in Appendix Table A5 for a daily analysis, show almost no effect of air quality warnings on the city's particulate matter concentrations.

6.4 Newey-West Standard Errors

There is a possibility that certain particles may linger in the atmosphere for extended periods, taking more than 24 hours to settle down, particularly in the case of $PM_{2.5}$. This introduces a temporal structure in the pollution data that must be considered when estimating the impact of policies aimed at reducing air pollution. Therefore, we adjust Equation (1) using a Newey-West estimator (Newey and West, 1986), which accommodates potential autocorrelation in the error terms. We present the results of this adjustment for the most significant episode, *Emergencies*, as it has shown statistical significance thus far. The results for both daily and hourly analyses for our preferred linear RD specification (e.g., columns (3) in Panels A and B of Tables 6 and 9) are in Appendix Tables A6 and A7, respectively. As observed, the estimates remain statistically significant at the 1% level in all cases, regardless of how we model the autocorrelation (number of lags). Therefore, our findings are not sensitive to the time structure of the data.

6.5 Falsification Test: Fake Cut-off Points

Thus far, the estimation results for air quality emergencies demonstrate robustness in terms of both sign and magnitude. However, to further validate this result, we assess its validity by shifting the cutoff in the RD estimation to a different time period, which should yield statistically insignificant results. We perform this falsification test by moving the effective day in which an environmental *Emergency* was issued to two days and one day before and after. The results in Table 12, using a linear polynomial, demonstrate that these fake cutoffs yield no significant impact on hourly pollution concentrations, thus reaffirming the validity of our previous result.

[3] One possibility, however, is that these recommendations lead to an aversion behavior where people reduce their use of wood-burning devices. Yet, there are no reasons to think that this aversion behavior will be more relevant in the case of alerts relative to the other stringent episodes.

Table 12: The Impact of Emergencies on Hourly Pollution Concentrations: Fake Cutoffs

	(1)	(2)	(3)	(4)
Panel A: $\mathbf{PM_{10}}$				
1[Emergency]	-0.280	0.149	0.248	-0.0347
	(0.236)	(0.201)	(0.166)	(0.162)
N	6,364	6,364	6,364	6,364
Panel B: $\mathbf{PM_{2.5}}$				
1[Emergency]	-0.233	-0.112	0.00849	0.0115
	(0.250)	(0.298)	(0.0459)	(0.146)
N	6,379	6,379	6,379	6,379
Controls	✓	✓	✓	✓
Station fixed-effects	✓	✓	✓	✓
Time fixed-effects	✓	✓	✓	✓
Fake Cut-off points	-48	-24	24	48
Bandwidth (panel A)	26.14	30.32	26.66	40.31
Bandwidth (panel B)	27.81	26.13	27.50	37.49

Notes: This table presents the impact of air quality *Emergencies* on the (logged) hourly average concentrations of particulate matter using fake cut-off points. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, day of the week, and hour of the day). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Clustered standard errors by station in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

7 Conclusion

Despite the extense body of evidence linking particulate matter exposure to adverse health effects, a considerable portion of the global population, especially in low-income countries, still relies on highly polluting fuels for cooking and heating. This study assesses the short-term impact of wood-burning restrictions, prompted by air quality warnings, on fine and coarse particulate matter levels during winter in Los Angeles, Chile.

We find that prohibitions on wood burning significantly reduce particulate matter concentrations, particularly during the strongest air quality warnings classified as emergencies. Specifically, we observe substantial reductions in daily pollution levels during emergencies, with decreases of 34.7% and 34.9% for PM_{10} and $PM_{2.5}$ respectively. Similarly, hourly analyses indicate significant reductions of 40% and 27% for PM_{10} and $PM_{2.5}$ concentrations, respectively, during emergencies. Notably, this short-term impact is more pronounced during nighttime, suggesting higher effectiveness when wood-burning heaters are likely to be in use.

While our findings underscore the effectiveness of the strongest air quality warnings in mitigating pollution, it is crucial to acknowledge the persistently high pollution levels in the city. Limited effectiveness of milder warnings underscores the necessity for more stringent measures to achieve substantial pollution reductions.

Our findings underscore the crucial need for implementing targeted and stringent measures to effectively address air pollution, particularly in regions where wood burning plays a significant role in deteriorating air quality, such as southern Chile. Conducting a comprehensive cost-benefit analysis, which takes into account the detrimental impacts of air pollution exposure, would greatly enhance the evaluation of command-and-control policies like the one examined in this study. Even in cases where such policies may not prove to be cost-effective, they can still effectively achieve their intended goal of reducing pollution and safeguarding public health.

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Appendix

Table A1: Descriptive Statistics of Hourly Weather Controls

Variable	N	Mean	Std. Dev.	Min	Max
Panel A: Full Sample					
Wind Speed	77,907	2.24	1.42	.003	10.449
Temperature	83,604	13.62	6.87	-4.92	39.27
Humidity	83,604	71.34	22.18	6.956	100
Panel B: Days Before *Pre-emergencies*					
Wind Speed	3,942	1.49	1.38	.012	10.449
Temperature	4,782	7.73	4.53	-3.98	23.35
Humidity	4,782	84.09	15.77	22.29	100
Panel C: Days with *Pre-emergencies*					
Wind Speed	3,945	1.13	0.94	.006	7.039
Temperature	4,785	7.78	4.66	-4.92	22.35
Humidity	4,785	84.75	15.41	24.76	100
Panel D: Days Before *Emergencies*					
Wind Speed	624	0.85	0.78	.0122	5.732
Temperature	912	5.79	5.07	-3.28	21.90
Humidity	912	86.35	14.59	30.17	100
Panel E: Days with *Emergencies*					
Wind Speed	624	1.27	0.95	.049	6.429
Temperature	912	6.31	3.77	-2.848	16.39
Humidity	912	89.27	10.69	54.16	100

Notas: This table displays descriptive statistics of meteorological variables on an hourly basis between 2018 and 2022. Panel A presents data for the entire period of the variables. Panel B shows data for the variables during the days preceding a *Pre-emergency*. Panel C presents data during an *Emergency*. Wind speed is in meters per second (m/s). Temperature is in degrees Celsius (°C). Humidity is in percentages (%). Data obtained from SINCA.

Table A2: The Impact of Air Quality Warnings on Daily Pollution Concentrations: Heterogeneous Effects by Year

	Panel A: PM_{10}			**Panel B: $PM_{2.5}$**		
Year	Episode	Pre-emergency	Emergency	Episode	Pre-emergency	Emergency
2019	0.00220	-0.0189	-0.375*	-0.0950	-0.137	-0.355*
	(0.0749)	(0.0756)	(0.191)	(0.123)	(0.122)	(0.197)
2020	0.102	0.0920	0.129	0.0727	0.0271	0.0311
	(0.0758)	(0.0759)	(0.150)	(0.111)	(0.111)	(0.157)
2021	-0.0159	-0.0263	0.0747	-0.151	-0.151	0.0110
	(0.0731)	(0.0753)	(0.121)	(0.121)	(0.127)	(0.130)
2022	0.0817	0.0509	-0.388**	-0.0890	-0.134	-0.691***
	(0.0773)	(0.0781)	(0.195)	(0.127)	(0.125)	(0.245)
N	1,405	1,379	626	1,413	1,387	629
Controls	✓	✓	✓	✓	✓	✓
Station fixed-effects	✓	✓	✓	✓	✓	✓
Time fixed-effects	✓	✓	✓	✓	✓	✓
Bandwidth	5.564	5.344	4.215	3.575	3.643	5.822

Notes: This table presents the impact of air quality warnings (pooled episodes, pre-emergencies, and emergencies) on the (logged) daily average concentrations of particulate matter allowing for heterogeneous effects by year. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, and day of the week). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Clustered standard errors by station in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: The Impact of Air Quality Warnings on Hourly Pollution Concentrations: Heterogeneous Effects by Hour of the Day

	Panel A: PM_{10}			**Panel B: $PM_{2.5}$**		
Hours	Episodes	Pre-emergency	Emergency	Episodes	Pre-emergency	Emergency
0:00≤ h< 3:00	-0.0120	-0.0205	-0.0326***	-0.0227***	-0.0186***	-0.0298***
	(0.0579)	(0.0577)	(0.00510)	(0.00448)	(0.00384)	(0.00640)
3:00≤ h< 6:00	-0.0101**	-0.0120***	-0.0237***	-0.0135***	-0.0145***	-0.0262***
	(0.00485)	(0.00371)	(0.00573)	(0.00415)	(0.00400)	(0.00671)
6:00≤ h< 9:00	-0.00434	-0.00574*	-0.00933	-0.00487	-0.00605	-0.0192***
	(0.00349)	(0.00346)	(0.00630)	(0.00412)	(0.00393)	(0.00683)
9:00≤ h< 12:00	-0.00726**	-0.00898***	-0.0119**	-0.0146***	-0.0161***	-0.0101
	(0.00317)	(0.00315)	(0.00530)	(0.00399)	(0.00357)	(0.00650)
12:00≤ h< 15:00	-0.00336	-0.00343	-0.00390	-0.00685*	-0.00652*	-0.00504
	(0.00314)	(0.00313)	(0.00420)	(0.00387)	(0.00366)	(0.00560)
18:00≤ h< 21:00	-0.0114***	-0.0106***	-0.0114***	-0.00732*	-0.00901**	-0.00629
	(0.00344)	(0.00328)	(0.00409)	(0.00379)	(0.00369)	(0.00490)
21:00≤ h≤ 23:00	-0.0173***	-0.0207***	-0.00933**	-0.00859**	-0.0130***	-0.00548
	(0.00373)	(0.00375)	(0.00396)	(0.00382)	(0.00322)	(0.00482)
N	22,210	21,559	6,333	22,210	21,559	6,333
Controls	✓	✓	✓	✓	✓	✓
Station fixed-effects	✓	✓	✓	✓	✓	✓
Time fixed-effects	✓	✓	✓	✓	✓	✓
Bandwidth	43.80	45.37	9.03	37.50	49.03	15.28

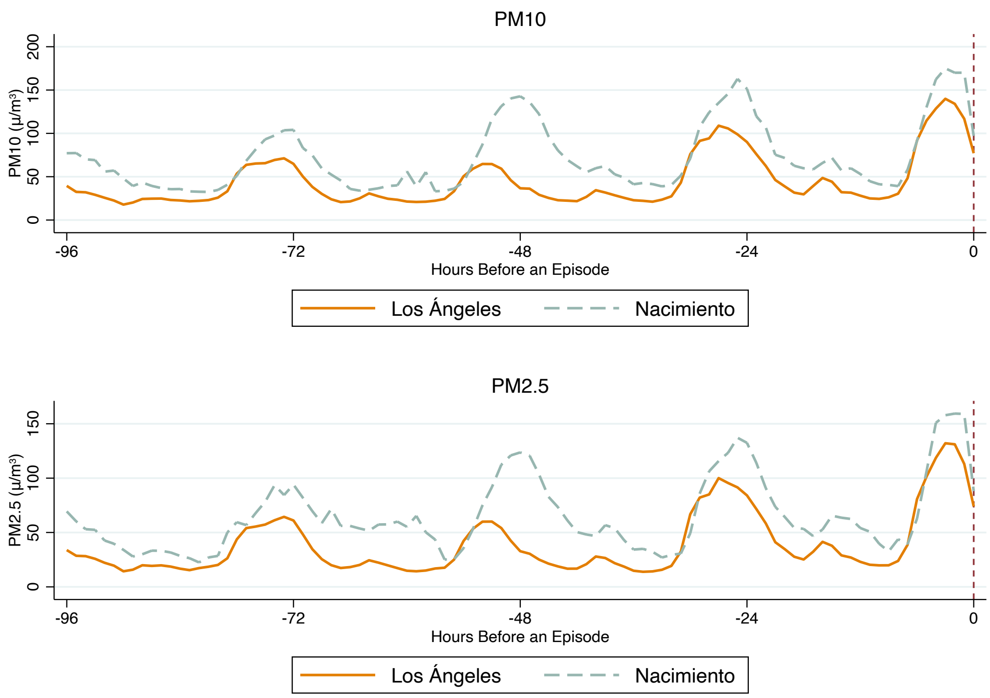
Notes: This table presents the impact of air quality warnings (pooled episodes, pre-emergencies, and emergencies) on the (logged) hourly average concentrations of particulate matter allowing for heterogeneous effects by hours. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, day of the week, and block of hours of the day). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Clustered standard errors by station in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A4: The Impact of Air Quality Warnings on 1-Day Lead Pollution Concentrations

	Episodio		Pre-emergencia		Emergencia	
Panel A: PM_{10}						
1[Episode]	-0.105	-0.192	-0.0409	-0.109	-0.463***	-0.575***
	(0.138)	(0.149)	(0.119)	(0.119)	(0.0108)	(0.0894)
N	1,405	1,405	1,379	1,379	622	622
Panel B: $PM_{2.5}$						
1[Episode]	-0.123	-0.208	-0.0591	-0.129	-0.444***	-0.537***
	(0.114)	(0.138)	(0.0869)	(0.0860)	(0.0561)	(0.176)
N	1,413	1,413	1,387	1,387	625	625
Controls	✓	✓	✓	✓	✓	✓
Station fixed-effects	✓	✓	✓	✓	✓	✓
Time fixed-effects	✓	✓	✓	✓	✓	✓
Order polyn.	1	2	1	2	1	2
Statistics Panel A:						
Mean left	53.88	53.88	52.69	52.69	52.31	52.31
Mean right	34.89	34.89	34.49	34.49	34.36	34.36
Bandwidth	3.604	6.257	3.807	7.214	4.457	7.459
Statistics Panel B:						
Mean left	40.04	40.04	39.11	39.11	39.83	39.83
Mean right	16.69	16.69	16.17	16.17	16.56	16.56
Bandwidth	3.902	5.724	4.266	7.262	4.187	7.177

Notas: This table presents the impact of air quality warnings (pooled episodes, pre-emergencies, and emergencies) on the (logged) 1-day lead average concentrations of particulate matter. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, and day of the week). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Clustered standard errors by station in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Figure A1: Hourly PM_{10} and $PM_{2.5}$ Average Concentrations for Treated and Control Cities Before the Treatment



Notes: This figure shows hourly PM_{10} and $PM_{2.5}$ concentrations for Los Ángeles (treated city) and Nacimiento (control city) 4 days before an air quality warning (episode) is issued. PM is measured in micrograms per cubic meter. Data come from SINCA.

Table A5: The Impact of Alerts on Daily Pollution Concentrations

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: PM$_{10}$						
1[Alerts]	0.175	0.0307	0.0259	0.185	-0.0238	0.0449
	(0.321)	(0.360)	(0.0502)	(0.345)	(0.352)	(0.0545)
N	1,379	1,379	1,379	1,379	1,379	1,379
Panel B: PM$_{2.5}$						
1[Alerts]	0.227	0.0835	0.0327	0.166	0.0572	0.0796*
	(0.636)	(0.698)	(0.0279)	(0.616)	(0.671)	(0.0484)
N	1,390	1,390	1,390	1,390	1,390	1,390
Controls		✓	✓		✓	✓
Fixed Effects Station			✓			✓
Fixed Effects Time			✓			✓
Order of polynomial	1	1	1	2	2	2
Statistics Panel A:						
Mean left	36.06	36.06	36.06	36.06	36.06	36.06
Mean right	35.47	35.47	35.47	35.47	35.47	35.47
Bandwidth	7.395	8.394	2.131	8.836	11.60	6.289
Statistics Panel B:						
Mean left	23.34	23.34	23.34	23.34	23.34	23.34
Mean right	17.09	17.09	17.09	17.09	17.09	17.09
Bandwidth	16.54	20.18	4.382	12.37	13.44	5.482

Notes: This table presents the impact of air quality *Alerts* on the (logged) daily average concentrations of particulate matter. Panel A shows the results for PM$_{10}$. Panel B shows the results for PM$_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, and day of the week). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Clustered standard errors by station in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A6: The Impact of Emergencies on Daily Pollution Concentrations: Newey-West Estimator

	(1)	(2)	(3)	(4)
Panel A: PM_{10}				
1[Emergency]	-0.412***	-0.412***	-0.412***	-0.412***
	(0.141)	(0.136)	(0.140)	(0.144)
N	626	626	626	626
Panel B: $PM_{2.5}$				
1[Emergency]	-0.346***	-0.346***	-0.346***	-0.346***
	(0.114)	(0.113)	(0.110)	(0.110)
N	629	629	629	629
Controls	✓	✓	✓	✓
Station fixed-effects	✓	✓	✓	✓
Time fixed-effects	✓	✓	✓	✓
Lags (days)	0	7	14	28
Statisticis Panel A:				
Bandwidth	4.215	4.215	4.215	4.215
Statisticis Panel B:				
Bandwidth	4.150	4.150	4.150	4.150

Notes: This table presents the impact of air quality *Emergencies* on the (logged) daily average concentrations of particulate matter using a Newey-West estimator. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, and day of the week). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Newey-west standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A7: The Impact of Emergencies on Hourly Pollution Concentrations: Newey-West Estimator

	(1)	(2)	(3)	(4)
Panel A: PM_{10}				
1[Emergency]	-0.403***	-0.403**	-0.403**	-0.403**
	(0.131)	(0.188)	(0.199)	(0.203)
N	6,333	6,333	6,333	6,333
Panel B: $PM_{2.5}$				
1[Emergency]	-0.265***	-0.265*	-0.265*	-0.265*
	(0.100)	(0.149)	(0.159)	(0.161)
N	6,333	6,333	6,333	6,333
Controls	✓	✓	✓	✓
Station fixed-effects	✓	✓	✓	✓
Time fixed-effects	✓	✓	✓	✓
Lags (days)	0	4	8	12
Statistics Panel A:				
Bandwidth	9.025	9.025	9.025	9.025
Statistics Panel B:				
Bandwidth	15.284	15.284	15.284	15.284

Notes: This table presents the impact of air quality *Emergencies* on the (logged) hourly average concentrations of particulate matter using a Newey-West estimator. Panel A shows the results for PM_{10}. Panel B shows the results for $PM_{2.5}$. All regressions include weather controls (temperature, wind speed, humidity), and station and time fixed (year, month, day of the week, and hour of the day). Optimal bandwidth using MSE minimization (Calonico et al., 2014). Newey-west standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.