Quantifying the Health Effect of Information on Pollution Levels in Chile

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Abstract

In response to the detrimental health impacts of short-term exposure to high levels of pollution, several policies have been designed to address this concern. One such policy implemented by the Government of Chile that institutes temporary measures to reduce negative impacts of high levels of air pollution in the short run through both emissions restrictions and public information campaigns. The includes public announcement of days for which pollution is projected to exceed threshold levels on the day prior to such an 'Episode'. In this paper we separately identify the mortality reducing effects of Episode announcements that are purely information-driven from those that are attributable to improved air quality using propensity score matching and a difference-in-difference approach. Our results suggest that Episode announcements are associated with reduced mortality for all individuals (with at least two thirds of these deaths attributable to the elderly) and that the main driver of this result is an increase in avoidance behaviors.

1. Introduction

Various studies establish a link between short-term exposure to high levels of air pollution and detrimental impacts on human health (Currie et al. 2009; Neidell 2009; Graff Zivin and Neidell 2012; Schlenker and Walker 2016). Aside from the impact of exposure on health, short-term spikes in pollution may also be costly if individuals undertake behavioral changes to avoid such exposure (Graff Zivin and Neidell 2013). Several studies assess the effectiveness of short-term policy measures set by local governments to limit pollution exposure on days that exceed set pollution limits and a few attempt to disentangle the health and information channels of the effects they identify (Cutter and Neidell 2009; Graff Zivin and Neidell 2009; Mullins and Bharadwaj 2014). Particularly, Mullins and Bharadwaj (2014) find that a policy implemented by the Government of Chile that institutes temporary measures to reduce negative impacts of high levels of air pollution in the short run is effective at improving air quality in the short run. This policy, called the Plan de Prevención y Descntaminación Atmosférica (translated as the Plan to Prevent and Reduce Air Pollution (PPDA)), includes public announcement of days for which pollution is projected to exceed threshold levels on the day prior to such an "Episode". The term 'Episode' is used to include three event labels, "Alerts", "Pre-Emergencies" and "Emergencies", announced separately and distinguished to signal increasing levels of pollution threshold exceedance, respectively. On the day of an Episode, the government imposes several restrictions to reduce pollution levels (see Table 1 for detailed restrictions associated with each Episode level).

While the Government of Chile constructed and began to implement policies to that identified and announced pollution Episodes to address growing concerns of pollution in the early 1990s, the PPDA was published in 1997 after which the policy was strictly adhered. The Alert, Pre-Emergency and Emergency Episodes were designed to be announced if daily PM_{10} concentrations are predicted to exceed 195 $\mu g/m^3$, 240 $\mu g/m^3$ and 320 $\mu g/m^3$, respectively. To put these thresholds in context, the World Health

Organization's (WHO) guideline for daily mean PM_{10} is 50 $\mu g/m^3$ (WHO 2011). However, it is evident from Figure 1 that, despite the reduction in annual mean PM_{10} levels in Santiago after the implementation of the PPDA in 1997, mean PM_{10} concentrations exceeded 50 $\mu g/m^3$ in every year between 1989 and 2008. Prior to the establishment of the PPDA in 1997, Episodes announcements were generally inconsistent compared to the period after 1997. Between 1989 and 1997, PM_{10} levels exceeded 240 $\mu g/m^3$ on 148 days; however less than 60 of these days announced as Episodes. Comparatively, nearly 100% of days deemed Episodes between 1997 and 2008 were announced (see Figure 2). Since policy defining Episode announcement prior to the implementation of the PPDA was generally ineffective, Mullins and Bharadwaj (2014) find days in the post-PPDA period when Episodes were announced that are similar to days in the pre-PPDA period when Episodes should have been announced but were not and exploit this difference to identify the effect of an announcement on PM_{10} and mortality outcomes. According to Mullins and Bharadwaj's (2014) results, the PPDA is successful at reducing both PM_{10} concentrations and deaths, particularly among the elderly, in days following an Episode announcement in the Santiago Metropolitan Region. The impacts on mortality, however, capture the net effect of the policy, and they are not able to separately identify the benefits of the improved air quality and avoidance behaviors undertaken in response to pollution information.

With this paper we seek to separate the identification of the morbidity and mortality reducing effects of Episode announcement that are purely information-driven from those that are attributable to improved air quality. Using weather, pollution mortality, and hospitalization data in Chile, we investigate avoidance behaviors in response to the PPDA policy to quantify the value of the information. To identify an effect, we use propensity score matching and a difference-in-difference approach, similar to Mullins and Bharadwaj (2014). With propensity score matching we match periods following an Episode announcement to periods with similar pollution patterns that did not follow an announcement. Because the pollution conditions are (by construction) similar between matched periods, differences in response to health outcomes following an Episode (or match non-Episode period) can be attributed directly to the informational content of the Episode announcement and the resulting avoidance behaviors undertaken by the population in response to the provided information.

Our results extend the Mullins and Bharadwaj (2014) findings by providing new and integral information in the assessment of the overall effectiveness of the PPDA. To understand the short-term effectiveness of PPDA Episodes requires the disentanglement of the concentration-reducing and information-provision channels of impact. As air quality improvement and avoidance behaviors impose different costs on the economy and society, the correct attribution of the benefits of the Episodes is critical for the future management of the negative effects of air quality in Santiago. Additionally, our results are important for informing the implementation of short-term approaches for addressing spikes in air pollution in other major urban centers. Given the growing prevalence of extreme air pollution events in metro areas from Europe to Latin America and Asia, such a focused understanding of the Chilean success story is more important than ever.

2. Data and Methodology

2.1 Data Description

To identify the effects of episode announcements on mortality we combine observations on PM_{10} concentrations, weather, Episode announcements and mortality at the daily level from 1989 to 2008. The PM_{10} concentration data comes from Chile's Ministry of the Environment, which maintains data collected by the MACAM 1 and MACAM 2 monitor networks on PM_{10} concentrations prior to 1997 and after1997, respectively. The MACAM 2 network currently includes nine monitors spread across Santiago, specifically located to observe concentrations at both hotspot and typical pollution levels (Gramsch et al. 2006). However, only three sites were monitored consistently across our period of study; therefore, we use PM_{10} data from only these sites: Parque O'Higgins, La Paz (or Independencia) and Las Condes. We use the average daily mean PM_{10} concentration across all stations.

Since weather conditions are likely to be correlated with pollution levels and mortality, we include various weather controls in our analysis. We obtained hourly weather data from the Summary of the Day data series from the U.S. National Climatic Data Center (NCDC), and use daily mean wind, precipitation and temperature observations as controls. We also include information on Episode announcements with the PM_{10} and weather data. The Santiago Metropolitan Region's Ministry of Health provided the dates of each episode and corresponding pollution levels.

Finally, we use aggregate daily mortality data and merge it with the PM_{10} concentration, weather and Episode data. The mortality data are from the Chilean Ministry of Health's Department of Statistics and Health information. Data on deaths is available starting in 1992 while data on cause-of-death begins in 1994. The cause-of-death data includes information on date of death, age at death, and International Classification of Diseases (ICD) codes for primary and secondary causes of death. Table 2 details the means of variables used in our analysis for the pre-PPDA and post-PPDA periods.

2.2 Methodology

Our empirical strategy to identify the effect of Episode announcements on avoidance behavior is to compare mortality outcomes on the days after an Episode announcement to days after which no Episode announcement occurred. To this we match days immediately leading up to, the day of, and the day after an Episode announcement to days with observationally similar PM_{10} concentrations occurring prior to the implementation of the PPDA using propensity score matching. Then we use a difference-in-differences (DID) model to compare the difference in mortality outcomes in the days following an Episode to days following a matched non-Episode to identify the effect of information. Because the pollution conditions are (by construction) similar between matched periods, differences in response to health outcomes following an Episode (or match non-Episode period) can be attributed directly to the informational content of the Episode announcement and the resulting avoidance behaviors undertaken by the population in response to the provided information.

While there are number of occasions for which Episode announcements occur on consecutive days, we restrict our sample to include only Episodes that occurred without another Episode announcement within five days before or after to avoid potential confounding factors associated with consecutive Episode announcements. The Government of Chile announced ninety-one episodes during the post-PPDA period; however, with the restriction of stand-alone Episodes, our sample includes 35 of these Episodes. Graff Zivin and Neidell's (2009) results indicate that for consecutive Episode announcements, observed behavioral responses are typical most prevalent only on the first day of announcement, which suggests that using only stand-alone Episodes would capture the strongest effect of avoidance behavior on Episode announcement.

Since Episodes prior to the implementation of the PPDA in 1997 were largely inconsistent and ineffective, there are likely to be few close matches of Episode days between these periods. Additionally, matching Episode announcements in the pre-PPDA period to Episode announcements in the post-PPDA period would identify the differential effect of Episodes in both periods instead of the overall impact of Episode announcements. Therefore, to establish an appropriate counterfactual to Episodes announced in the post-PPDA period, we match PM_{10} concentrations on days immediately before, the day of and days immediately after an Episode announcement in the post-PPDA period to observationally similar days (but not Episode announcements) in the pre-PPDA period. While we cannot find exact matches between the pre- and post-PPDA period, propensity score matching allows us to identify similar matches (Rosenbaum and Rubin 1983). We estimate a Logit model to predict the probability that an Episode is announced on any given day based on PM10 concentrations five days before, the day of and five days after an Episode. The specify the following model:

$$(1)\; y_t = \alpha + \sum_{j=1}^{5} \left(\beta_j * PM10_{t-j}\right) + \sum_{k=0}^{5} \left(\varphi_k * PM10_{t+k}\right) + \boldsymbol{DOW'}_t \delta + \boldsymbol{month'}_t\, \theta + \varepsilon_t$$

In this model y_t is an indicator that equals one if an Episode was announced on day *t* in the post-PPDA period, $PM10_{t-j}$ is the daily mean PM_{10} concentration *j* days before day *t* and $PM10_{t+k}$ is the daily mean PM_{10} concentration *k* days after day *t*. $\boldsymbol{DOW}_t$ and $\boldsymbol{month}_t$ are day-of-week and month-level fixed effects, respectively. We include the day-of-week fixed effects to account for potential dependence of Episode announcement based on the day-of-week while monthly fixed effects are included to capture seasonal variation in weather patterns and potentially Episode announcements. $\alpha, \beta_j, \varphi_k, \delta$ and θ are estimated coefficients and ε_t is the error term.

Using the coefficients estimated by the Logit model, we plug the observed values for each pre- and post-PPDA episode into the model to obtain the predicted value of y_t, which is the propensity score for day *t*. We use the Nearest Neighbor approach to identify the five closet matches of days in the post-PPDA period to days in the pre-PPDA period. Including multiple matches reduces variance; however, larger values of n-Nearest neighbors can reduce the quality of the matches. To further ensure quality of matches, we include only matches with a common support, which results in dropping one post-PPDA Episode, and our final sample for the difference-in-difference regressions includes 32 post-PPDA events (Heckman, LaLonde and Smith 1999). Table 3 compares the mean PM_{10} concentrations in the five days before, day of, and five days after an Episode (the matching criteria) in the control (Episode days) and treatment groups (matched non-Episode days). Table 3, along with Figure 3, provides supports that our matches do have observationally similar PM_{10} concentrations across the compared days.

Finally, we implement the DID regressions to compare the difference in mortality outcomes in the five days following an Episode to the five days following a matched non-Episode to identify the effect of information. The DID approach allows us to appropriately compare mortality outcomes in the treatment and control groups by controlling for systematic differences between the groups. This strategy first differences the mortality outcomes for days before and after an Episode (treatment group) or non-Episode (control group). Then the difference between these two groups gives the effect of an Episode announcement on mortality outcomes. To further control for systemic differences between the treatment and control groups we include weights from the matching procedure in the DID regressions (Hirano and Imbens 2001; Imbens 2004). We run the DID regressions on six different sample, where each sample captures the effect on mortality on different days following an Episode up to five days, for which each sample includes one day before an Episode (t=-1) and one day of or after (t = 0, 1, 2, 3, 4, or 5). For instance, the first regression captures the difference in mortality between the day of an Episode and the day prior. The second regression examines the difference in mortality between the day after an Episode and the day prior, and so on. The sixth regression represents the difference in mortality between five days after an Episode and the day prior. Additionally, we examine ten different mortality outcomes: all ages for all causes of death, all ages for deaths caused by respiratory illnesses, all ages for deaths caused by circulatory illnesses, all ages for deaths caused by cancer, all ages for deaths caused by accidents, and all of the above but for a subsample of the population over 64. Therefore, we estimate 60 regressions in total. Using ordinary least squares, the DID specification for the six samples and 10 different mortality outcomes is:

$$(2)\ Y_{it} = \alpha + \eta * E_i + \omega * P_t + \rho * (P_t * E_i) + \sum_{j=1}^{4}\left(\beta_j * PM10_{i-j} + \boldsymbol{X'}_{\boldsymbol{i-j}}\gamma_j\right) + \sum_{k=-1}^{t}(\varphi_k * PM10_t + \boldsymbol{X'}_{\boldsymbol{t}}\tau_k) + \boldsymbol{DOW'}_i\delta + \boldsymbol{month'}_{it}\,\theta + \varepsilon_{it}$$

In this model *i* indicates the date of an Episode (in treatment group) or matched "non-Episode" (in control group), which we will continue to refer to each occurrence as a "pollution event", and *t* is the distance of the sample observation from the associated pollution event *i*, where *t* can take the values -1, 0, 1, 2, 3, 4 or 5. Y_{it} is a mortality outcome for day *t* relative to a pollution event *i*. E_i is an indicator that equals one if the observed day is associated with an Episode that occurred in the Post-PPDA period, and zero if the observed day is a day before or after a non-Episode in the pre-PPDA period. P_t is an indicator that equals one if the observed day occurred on or after a pollution event ($t \geq 0$), and zero if the observed day is before a pollution event (t < 0). $(P_t * E_i)$ is an interaction term representing the effect of mortality on the day of or days following an Episode, and is the coefficient of interest in each regression. The term, $\sum_{j=1}^{4}\left(\beta_j * PM10_{i-j} + \boldsymbol{X'}_{\boldsymbol{i-j}}\gamma_j\right) + \sum_{k=-1}^{t}(\varphi_k * PM10_t + \boldsymbol{X'}_{\boldsymbol{t}}\tau_k)$, indicates inclusion of PM_{10} concentration and weather values for the five days preceding event *i* and then PM_{10} concentration and weather values for the days after event *i* up to the contemporaneous value for each regression. As in the Logit model, $\boldsymbol{DOW}_i$ and $\boldsymbol{month}_i$ are day-of-week and month-level fixed effects, respectively. $\alpha, \eta, \omega, \rho, \beta_j,\ \gamma_j, \varphi_k,\ \tau_k, \delta$ and θ are estimated coefficients and ε_{it} is the error term.

3. Results and Discussion

Tables 4 and 5 summarize the main results from the difference-in-difference regressions. Each cell in Table 4 and 5 represent a coefficient (the coefficient of interest from Equation 4, ρ) from a different regression. Table 4 includes results from the regressions on deaths for all ages while Table 5 includes mortality outcomes for a subpopulation of individuals over 64, which potentially represents a more health-sensitive group to pollution spikes. In the first columns of Tables 4 and 5, the coefficients are statistically significant and negative, suggesting that Episode announcements are associated with reduced mortality for all individuals, and at least two thirds of these deaths are attributable to the elderly.

That deaths are significantly lower in treatment group (Episodes were announced in response to pollution spikes) compared to control (Episodes were not announced in response to pollution spikes), suggests people are experiencing less pollutant exposure. In the treatment and control group people are being exposed to same PM10 levels after an episode and on matched days (by construction of matched days). Since deaths are reduced in the treatment group, this suggests people are staying inside in response to the episode information and getting near-zero PM_{10} exposure as opposed to some PM_{10} exposure. Average PM_{10} levels after an episode and on matched days appear to be between 90-100 $\mu g/m^3$ (see Figure 3). As the WHO guideline for PM10 is 50 $\mu g/m^3$ (WHO 2011), going outside after an episode could still be harmful, and we might not see significant reductions in death even due to episodes if individuals are not engaging in avoidance behavior.

Additionally, examining the cause of death, respiratory related deaths represent about one third of the drop in deaths. Coefficients on circulatory and cancer related deaths are statistically insignificant; however, accidental deaths among the elderly appear to increase immediately after an Episode announcement. An increase in accidental deaths, particular among the elderly, could be a result of higher levels of public transport and street sweeping are provided, leading to increased pedestrian related accidents. These types of accidents are much more likely to lead to death than accidents between cars, especially in urban environments where traffic speeds generally aren't that high. Therefore, an increase in pedestrian accidents does not necessarily contradict that individuals are not undertaking avoidance behaviors in response to Episode announcements.

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Appendix

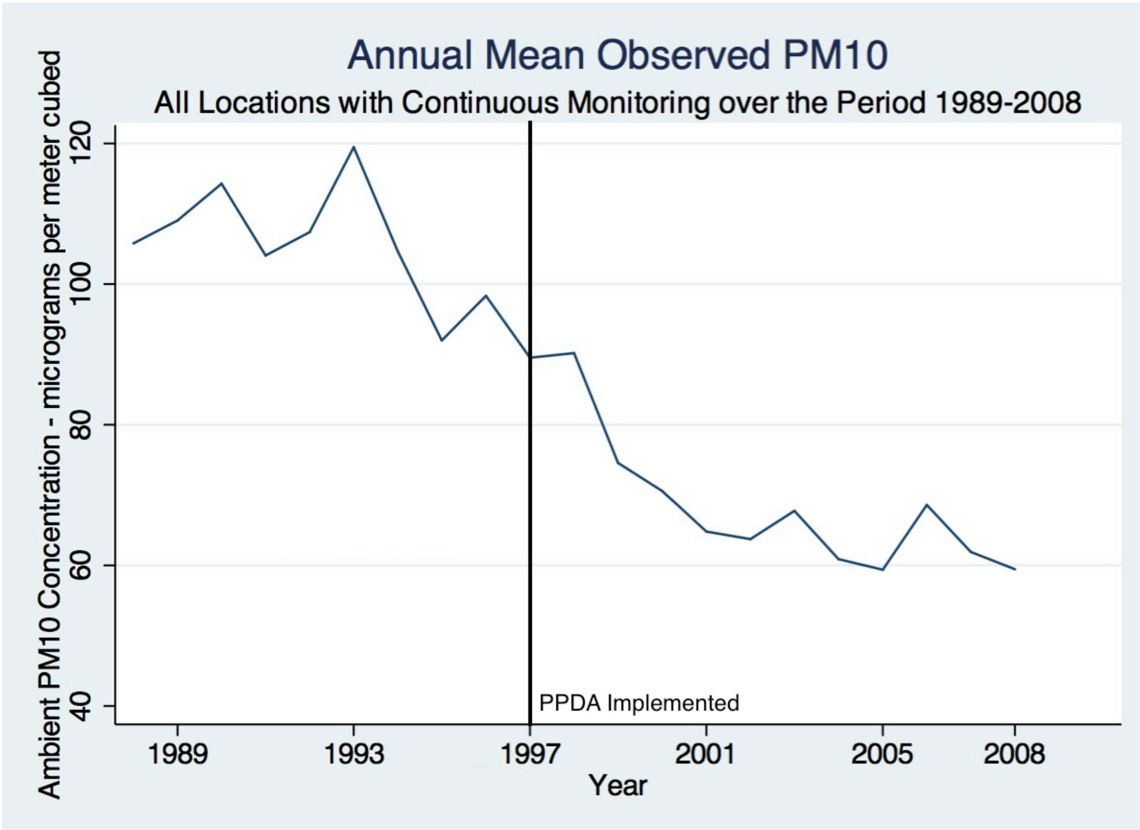

Figure 1. Annual Mean PM_{10} Concentrations in Santigo Adapted from Mullins and Bharadwaj (2014)

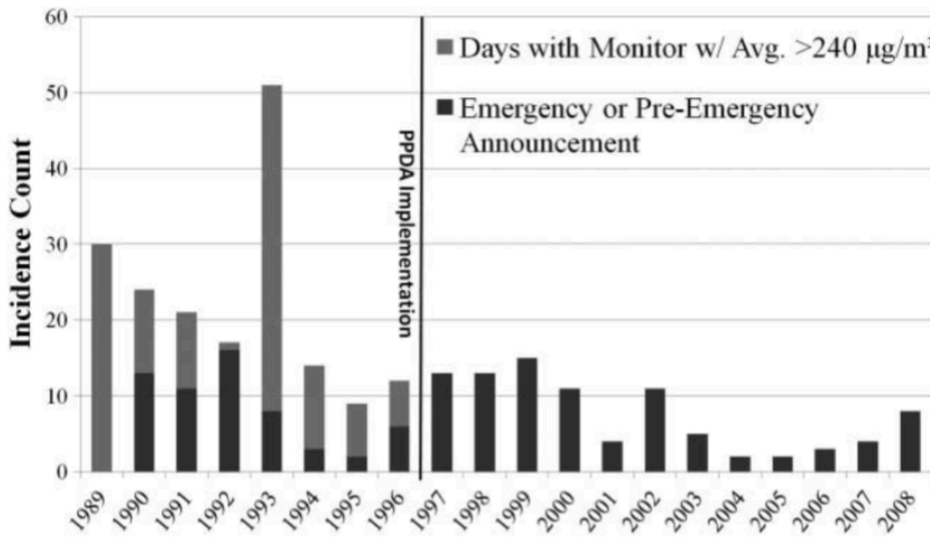

Figure 2. Warranted Episode Occurrences and Announcements Before and After PPDA Implementation from Mullins and Bharadwaj (2014)

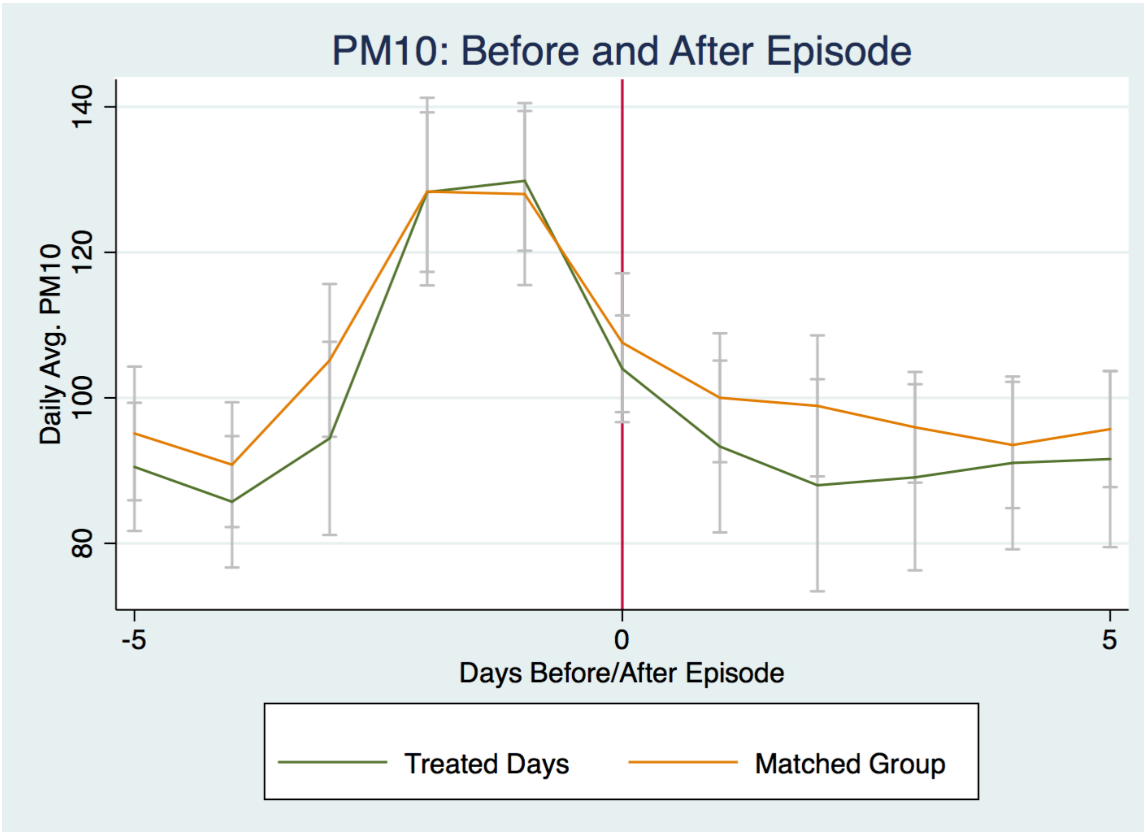

Figure 3. Comparison of Daily Mean PM_{10} Levels for Treatment and Control Groups

Table 1. Temporary Plans and Restrictions Implemented According to the PPDA Adapted from Mullins and Bharadwaj (2014)

Episode Level	Protocols
Alert PM_{10}>195 µg/m^3	-Use restriction on vehicles w/o catalytic converters: 40% week, 20% weekends -No use of uncertified residential wood or biomass heating
Pre-Emergency PM_{10}>240 µg/m^3	-Use restriction on vehicles w/o catalytic converters: 60% week, 40% weekends -Use restrictions on vehicles with catalytic converters: 20% all days -Operation ban on stationary emissions sources contributing 30% of total stationary emissions of particulate matter -Potential suspension of Physical Education classes community sports -More intense traffic and public transportation plans in effect -Stricter enforcement on mobile & stationary sources of air pollution -Increased street sweeping and cleaning activities -Increased Metro service -No use of uncertified residential wood or biomass heating
Pre-Emergency PM_{10}>330 µg/m^3	-Use restriction on vehicles w/o catalytic converters: 80% week, 60% weekends -Use restrictions on vehicles with catalytic converters: 40% all days -Operation ban on stationary emissions sources contributing 50% of total stationary emissions of particulate matter -Potential suspension of Physical Education classes community sports -More intense traffic and public transportation plans in effect -Stricter enforcement on mobile & stationary sources of air pollution -Increased street sweeping and cleaning activities -Increased Metro service

Table 2. Comparison of Means Before and After PPDA Implementation for Variables Used in Analysis

	1989-1996	1997-2008
Daily Mean PM_{10} ($\mu g/m^3$)	106.15	69.28
Daily Temperature (°F)	57.85	58.41
Daily Wind Speed (knots)	4.72	4.80
Daily Precipitation (inches)	0.03	0.03
Daily Deaths	77.15	85.79
Daily Deaths Over 64	47.70	57.45
Daily Respiratory Deaths	10.20	9.22
Daily Respiratory Deaths Over 64	7.90	7.76
Daily Circulatory Deaths	21.76	23.92
Daily Circulatory Deaths Over 64	17.23	19.12
Daily Cancer Deaths	17.21	20.17
Daily Cancer Deaths Over 64	10.72	13.22
Daily Accidental Deaths	7.98	5.63
Daily Accidental Deaths Over 64	1.45	1.19
Avg. Population	5,496,505	6,342,665
Avg. Population Over 64	343,922	469,945
Avg. # Emergency Episodes per Year	0.75	0.17
Avg. # Pre-Emergency Episodes per Year	6.63	7.42

Table 3. Balance Table Comparing Means for Treatment and Control Groups

			Means			t-test for Equal Means	
		Variable	Treated	Control	Percent Bias	t-stat	p-value
Lag	5	PM10	90.511	92.365	-4.4	-0.21	0.833
	4	PM10	85.716	91.017	-12.6	-0.59	0.559
	3	PM10	128.28	141.83	-30.1	-1.02	0.313
	2	PM10	128.28	141.83	-30.1	-1.02	0.313
	1	PM10	129.83	142.33	-28.6	-0.9	0.371
Lead	0	PM10	103.99	111.39	-18.1	-0.77	0.446
	1	PM10	93.316	99.991	-15	-0.65	0.515
	2	PM10	87.985	92.22	-8.8	-0.39	0.701
	3	PM10	89.077	94.34	-11.5	-0.55	0.586
	4	PM10	91.054	94.977	-8.4	-0.39	0.699
	5	PM10	91.587	95.269	-8	-0.37	0.711
Observations			32	94			

Table 4. Effects of Episode Announcements on Deaths for Individuals of All Ages

	All Ages				
	Cum. All Deaths	Cum. Respiratory Deaths	Cum. Circulatory Deaths	Cum. Cancer Deaths	Cum. Accidental Deaths
Difference from Day before to Day of Episode	-6.888*	-0.556	1.616	-3.302	0.223
	(3.67)	(1.75)	(2.20)	(2.19)	(1.00)
Difference from Day -1 to Day 1	-21.324***	-3.004	-3.182	-4.291	-0.129
	(7.72)	(3.18)	(3.99)	(4.63)	(2.52)
Difference from Day -1 to Day 2	-30.595***	-7.817*	-3.668	-3.937	-0.447
	(11.14)	(4.32)	(5.79)	(5.84)	(3.36)
Difference from Day -1 to Day 3	-35.582**	-13.023**	-3.978	-2.563	1.367
	(14.31)	(4.91)	(6.41)	(8.27)	(4.24)
Difference from Day -1 to Day 4	-47.485**	-16.004**	-3.814	-9.017	0.633
	(19.85)	(7.07)	(9.80)	(10.28)	(5.38)
Difference from Day -1 to Day 5	-54.830**	-18.846*	0.205	-14.392	-1.527
	(24.93)	(9.41)	(14.71)	(12.74)	(7.01)
Pre-Episode Daily Mean	94.14	12.74	27.44	20.35	4.43
N	118	96	96	96	96
Treatment	32	32	32	32	32
Control	86	64	64	64	64

* Significant at 0.10
**Significant at 0.05
*** Significant at 0.01

Table 5. Effects of Episode Announcements on Deaths for Individuals Aged 64 or Older

	Deaths Age Over 64				
	Cum. All Deaths	Cum. Respiratory Deaths	Cum. Circulatory Deaths	Cum. Cancer Deaths	Cum. Accidental Deaths
Difference from Day before to Day of Episode	-3.339	0.145	1.683	-2.481	0.484
	(2.79)	(1.44)	(1.96)	(1.82)	(0.51)
Difference from Day -1 to Day 1	-14.569**	-2.618	-2.579	-2.19	1.181
	(6.41)	(2.64)	(3.34)	(3.70)	(0.92)
Difference from Day -1 to Day 2	-19.231**	-7.460**	-1.935	-1.303	2.302
	(8.77)	(3.45)	(5.03)	(4.60)	(1.47)
Difference from Day -1 to Day 3	-28.443**	-12.147***	-2.249	-0.203	3.802**
	(12.05)	(3.94)	(6.27)	(7.16)	(1.65)
Difference from Day -1 to Day 4	-37.482**	-13.951***	-3.389	-6.195	4.409*
	(16.54)	(4.89)	(9.17)	(7.92)	(2.24)
Difference from Day -1 to Day 5	-41.619**	-15.737**	0.656	-7.914	3.333
	(19.73)	(7.12)	(13.37)	(8.33)	(3.10)
Pre-Episode Daily Mean	64.49	10.97	22.28	13.31	1.05
N	118	96	96	96	96
Treatment	32	32	32	32	32
Control	86	64	64	64	64

* Significant at 0.10
**Significant at 0.05
*** Significant at 0.01