Economic disparities in pollution-related mortality in three municipalities of the Mexico City Metropolitan Area

Alejandro Islas-Camargo
Department of Statistics, ITAM, Mexico

Alok K. Bohara
Department of Economics and the RWJF Center for Health Policy at the University of New Mexico, USA

J. Mario Herrera Ramos
FLACSO, Mexico

Abstract

In this study, we explored the nature of the health risk among the population of three municipalities of the Mexico City Metropolitan Area (MCMA) through an empirical assessment of the health impacts of air pollution and temperature variation. Based on the environmental justice theory we asked whether in very unequal socioeconomic municipalities of the MCMA, the association between PM_{10} concentration and mortality depend on socioeconomic disparities. We differ from what usually have been doing on these studies by using a state-space model instead of the Poisson regression model. The state-space model allows us to estimate the size of the unobserved at-risk population, its hazard rate, life expectancy of individuals in that population, and the effect of changes in environmental conditions on that life expectancy. Our results show a lower hazard rate in the wealthy municipality compared to the higher hazard rate in the poor one. The lower hazard rate of the wealthy municipality lengthens life expectancy and allows individuals to stay longer in the at-risk population, thereby making that population larger than the at-risk population of the poor municipality whose individuals have lower life expectancy. This happened because the proposed state-space model assumed that all deaths must first be susceptible, so the smaller the at-risk population the grater the individual probability of death. This means that the smaller the at-risk population the sicker its average member, and hence the smaller the impact on long term mortality. Our study that examines how health disparities play out regionally could have implications for the development of policy initiatives that ameliorate fundamental drivers of environmental health and disease among diverse communities.

Key words: mortality displacement; Poisson model; state-space model; environmental justice; health disparities.

1. Introduction.

Many studies have found association between ambient Particulate Matter (PM) concentration and mortality at metropolitan areas that has been interpreted as the response in a population of individuals with fragile health, such as person with chronic cardiac or respiratory diseases and the elderly (Environmental Protection Agency, 1996). This means that part of the association reflects the shortening of life expectancy by only a few days. This effect termed the "Mortality displacement" has been suggested as the only interpretation of the acute association between air pollutant and mortality, and has led to reluctance to enhance emission controls. Such a policy implications stresses the need to quantify the shortening of life expectancy implied by the evidence relating air pollution to mortality.

If the statistical association between exposure and mortality only reflected a few days shortening in the life expectancy at a population group already at high risk, the days following the air pollution episode should be marked with mortality below baseline levels. However, some studies provided counter evidence of this short-term mortality displacement hypothesis by showing that association between air pollution and mortality increases with the duration of the exposure (Schwartz 200, Dominici et al 2003). Moreover, the pattern of the association reported by these studies, implies that short term exposure to air pollution is not only responsible for a few days shortening of life expectancy but also for the transition from a healthy population to the at-risk population; challenging the hypothesis that air pollution effects are limited to the pool of very frail people.

The Mexico City Metropolitan Area (MCMA) with its high levels of urbanization and uneven distribution of wealth and resources is facing hazards and inequalities that naturally lead to the question of whether the health risks related to air pollution, particularly the mortality displacement hypothesis are socioeconomically differentiated within and across municipalities. After all, under the socioeconomic status underlies three major determinants of health: health care, environmental exposure, and health behavior. Moreover, chronic stress associated with lower socioeconomic status my also increase morbidity and mortality (Adler and Newman, 2002).

To explore whether the health risks associated with pollution are socioeconomically differentiated across municipalities of the MCMA, we refer to the theory of environmental Justice. The concept of environmental justices has been evolved from its initial goal focused on environmental discrimination to a wide variety of them. According to Schlosberg (2013) environmental justice in general means inequality in the distribution of negative effects of environmental damage, and therefore some population groups are at higher environmental risk than others. In these terms, environmental justice is just one of the many faces of social inequality. Schlosber argues that environmental justice since its beginnings has always being interested in other themes besides those inequities. The growing pressures of different environmental movements around the world have resulted in the expansion of the themes included in the theory of environmental justice. This expansion includes three main topics: The definition of environment, the factors that cause the generation of environmental injustice, and the different conception of justice that conform the concept of environmental justice (Schlosberg, 2013). In our work we adopt the traditional concept of environmental justice, namely, the association of a geographically localized relation between socially disadvantaged population and environmental pollution.

Understanding exposure variations among subpopulations is important for risk management, and environmental justice. Environmental health policy seeks not only to reduce population average risk, but also to ensure that specific subpopulations are not unduly burdened relative to the overall population. Policy makers concerned about environmental justice argue that communities who are segregated in neighborhoods with high levels of poverty and material deprivation are also disproportionately exposed to physical environment that adversely affects their health and well-being. They have also noted that groups with low socioeconomic status become concentrated, centralized, and isolated in abandoned inner city cores where employment opportunities are few and where communities are clustered around industrial sites, undesirable land use, and transportation corridors that pose significant health hazard (Pulido et al 1996).

The study of environmental inequalities is of particular importance for the MCMA for several reasons. First, there is no explicit recognition of environmental justice in any different laws, local and federal, related to the environment.

Second, the MCMA as all Mexican urban areas has two important characteristics for the study of pollution related mortality from the environmental justice point of view: (i) it is deeply segregated both socially and spatially and this phenomenon has been increasing throughout the years (Monkkonen 2012, Sánchez 2012a y 2012b, Rubalcava y Schteingart 2012); (ii) According to The National Council for the Evaluation of Social Development Policy (CONEVAL), about 34.4% of its population is living in poverty conditions and the elder people is even more segregated (Garrocho y Campos 2016). More than 18% of Mexico´s entire population lives in the MCMA, about 30% of the country´s industrial output is produced within its envious, and generates 23.6 of the country´s employment.

Third, there is wide evidence on health inequality in Mexico that support the existence of income related inequalities, inequalities in health, and in health care (Barraza-Lloréns, Panopoulou and Díaz 2013, PNUD 2011). Therefore, it is difficult no to take this fact into consideration given the close relationship between environmental justice and health inequality (Brulle and Pellow 2005, Wakefield and Baxter 2010).

Fourth, there are a few studies for the MCMA that explore whether the health risks related to air pollution are socioeconomically differentiated. A work related we our paper is the one of Romero et al (2013). These authors explored the nature of health risk among the population of Mexico City, Bogota and Santiago de Chile. They conclude that "*While proponents of the environmental justice perspective may expect that spatial differences in environmental hazards overlap with socioeconomic characteristics of human settlement, our results suggest the association between levels of air pollution and social vulnerabilities do not always hold within the study cities."* Their findings also suggest characteristics of a boomerang effect, i.e, affecting rich and poor alike. Even though we agree that pollution affect rich as well as poor people, our proposal shows some evidence in favour of environmental justice.

Finally, we think that environmental justice, both as analytical framework and as principle to design and evaluate environmental policies provides the right perspective to face some of the most urgent environmental problems that Mexican local governments need to solve.

Therefore, we hypothesize that the association between PM concentration and mortality in very unequal socioeconomic municipalities of the MCMA depend on socioeconomic differentiations. To test this hypothesis we select three municipalities of the MCMA, with high, middle and low income levels. From a public health perspective, the rationale for taking a municipality approach to examining links between socioeconomic status, environments, and health disparities is twofold: First, theory suggests that it is more successful to assesses divers of environmental health disparities at the regional level because economic trends, transportation planning, and industrial clusters tend to be regional in nature, actually zoning, facility siting, and urban planning decisions tend to be local (Morrelo-Froch et al 2002). Second, studies that examine how health disparities play out regionally could have implications for the development of policy initiatives that ameliorate fundamental drivers of environmental health and disease among diverse communities.

Our results show inconsistency with the displacement hypothesis for the high income municipality, which contends that the air pollution mortality association is caused entirely by frail persons dying a few days earlier than they would have absent pollution. This provides evidence of an impact not only to a susceptible pool of the population but also to the generally healthy individuals that are exposed to high levels of air pollution for sufficient amount of time my develop chronic conditions and enter the susceptible group. We found that the low socioeconomic municipalities tends to have high vulnerability to air pollution, that is, given exposure level may cause greater than average health reduction for these groups. The socioeconomic disparities between municipalities partially explain why we observe a lower hazard rate with high variability in the wealthy municipality compared to the higher hazard rate with low variability in the poor one. The lower hazard rate of the wealthy municipality lengthens life expectancy and allows individuals to stay longer in the at-risk population, thereby making that population larger than the at-risk population of the poor municipality whose individuals have lower life expectancy.

The paper is organized in three additional sections. Section 2, describes the climatic, atmospheric and socioeconomic conditions that makes these three municipalities sources of high disparities among them. It then characterizes the data applied to explore health risk. Section 3, describes the model used to estimate the relationship between particulate matter concentration and mortality. We propose a state-space model that allows us to estimate the size of the at-risk population, life expectancy of individuals in that population, and the effect of changes in air quality on that life expectancy. The empirical analysis and some concluding remarks are carried out in section 4.

2. Study Municipalities and Data

The MCMA is located in an elevated basin surrounded by mountain ridges on three sides (east, south, and west) with a broad opening to the north and a narrow gap to the south-southwest. The mountain and the frequent term inversions trap pollutant within the basin. In addition, the high altitude makes combustion sources less efficient. The tropical latitude (19° 25' N) and the high altitude (2240 m above the sea level) make sun light less intensive than in lower elevation, higher latitude cities (Molina and Molina , 2004). The climate is generally dry, but thunderstorms are frequent and intensive from June through October. Winters are slightly cooler than summers. Since specific humidity, temperature and win speed acted as clears of PM for the atmosphere, the safest period for the MCMA in terms of PM emissions is precisely from June through October.

Several criteria were used to select the three municipalities to evaluate if the health risks relations to air pollution are socioeconomically differentiated: To examine health risk we need to gather, validate and analyze air pollution, local temperature, and socioeconomic vulnerability data. Alvaro Obregon, Iztapalapa and Naucalpan de Juarez were those municipalities having the most complete data set to carry out our study.

With a population of 1,815,768 as of 2010 census, Iztapalapa is the most populous municipality of the MCMA, and it is also the most populous borough in Mexico. Over 92% of Iztapalapa's territory is urbanized, while Alvaro Obregon and Naucalpan de Juarez have 66% and 43.8% of their territory urbanized, respectively. Regarding industrial land use, 3.0%, 3.2% and 0.7% of the territory of Iztapalapa, Naucalpan de Juarez and Alvaro Obregon is used for industrial activity, respectively.

Being the most populous municipality, Iztapalapa has very demanding transportation requirements. Today, most transportation in the municipality is on various roadways via public and private vehicles. The main highway leaving Mexico City cuts through the municipality. Each day about 80,000 vehicles pass through, making it the second busiest highway section in the MCMA. The two most important economic activities in Iztapalapa are manufacturing and commerce. The largest sector of retail sales is in the street markets, followed by public markets and street peddlers that flagrantly violate sanitation and environmental laws. Industry includes food processing, tobacco products, metals, machinery, surgical equipment, paper and printing and textiles.

Naucalpan de Juarez is a municipality located just northwest of Mexico City in adjoining State of Mexico. At the 2010 census its total population was 833,779 inhabitants. Its subsoil is considered to be gravelly polluted, mostly due the “Bordo poniente” landfill and the sinking of the subsoil due to the over pumping of groundwater and the dumping of untreated wastewater. In addition, many small businesses such as brick making operations, public restrooms and restaurants flagrantly violate sanitation and environmental laws increases the pollution in the municipality. However, automobiles account for 70% of the air pollution. Stronger environmental regulations driven by a growing middle class have been enacted and enforced; this has led to the abandonment of the municipality by larger industries who have reallocated to the north and west of the MCMA. Industries which have left Naucalpan de Juarez include metals, cement, glass-work and others that use a large quantity of energy. About 20% of the manufacturing facilities have closed their doors and six industrial parks are empty.

Alvaro Obregon contains a large portion of the south-west part of Mexico City. It has a 2010 census population of 727,034 inhabitants. The municipality occupies 7,720 hectares, of such territory, 66.1% is urban soil and 38% is considered protected soil. Services (including financial services) make up the largest segment of the municipality economy, accounting for 75.6% of gross domestic product and employing about 76.14% of the workforce.

Table1 shows that while the variations in the average daily temperature of any of these municipalities are no large, the variations in the daily average pollution are high. For example, the daily average level of PM_{10} rage between 6.88 and 115.32 $\mu g/m^3$ in Alvaro Obregon, while for Iztapalapa the daily average level of PM_{10} rage between 7.00 and 268.00 $\mu g/m^3$. Large differences on pollution emissions will imply different hazard exposure on those municipalities. Urban vulnerability as impact studies have found that the risks of adverse health impacts depend on two series of factors. The first is related to the nature of the hazard to which urban populations are exposed, while the second is related to the socioeconomic conditions influencing exposure, sensitivity and capacity for responding to risk and health outcomes, which may reflect inequalities in access to services and welfare systems. Therefore, we need to understand the current baseline environmental and socioeconomic conditions of these municipalities.

Table 1 characterizes the three municipalities broken down by their levels of socioeconomic segregation using data from the 2000 and 2010 census as well as from the 2005 population and housing count. The first set of socioeconomic variables in Table 1 measures poverty characteristics and shows differences in average per-capita income between municipalities. The annual per-capita income in the wealthiest municipality is 1.25 times the one of the poorest municipality. There is however, important variability between households within each municipality and between municipalities. The GINI suggests that there is greater inequality in the two wealthiest municipalities, reflecting the more heterogeneous composition of the neighborhoods.

In term of demographic composition within neighborhoods, Table 1 shows that the population rate over 18 years with at least bachelor degree decreases as the proportion of poor households increases, as expected. Further, there is evidence that racial dynamics are at play. To a great extend this may reflect the low income of indigenous residents (in terms of the number of minimum wages[1]), but their high concentration in a few neighborhoods is highly suggestive of at least some elements of ethnic segregation.

Female labor force participation and the average of earned increases along with segregation in agreement with multiple studies that suggest that poor urban households have increased their labor supply in order to compensate for decreasing real income since

[1]The minimum wage is used as the base figure from which to calculate numerous other payments, such as fines or benefits and it is equal to 73.04 Mexican pesos or about 4.30 USD per day.

1980s. However, in contrast to the case of the United States, the average percentage of female-headed households is the same in wealthy and poor households. This is in agreement with studies showing that in Mexico, low-income single mothers tend to move in with other family members, forming extended families to cope with scarcity and family demands, studies also show that women in these conditions are seldom declared as the head of the household, regardless of their monetary contribution to the household.

Turning to employment patterns, Table 1 shows consistent link between socioeconomic segregation and character of employment, the more segregated a municipality is, the higher the percentage of informal employment workers. Thus people living in areas with higher concentration of poor households are likely to hold jobs that do not provide health insurance or pension contributions and therefore, they have lower level of health as indicated by the infant mortality rate. In general, these trends show the anticipated pattern of greater levels of precarious employment in poorest municipalities. However, unemployment does not highly rise with poverty; it remains at close levels across municipalities. This is not surprising in Mexico, were joblessness is more common among educated workers because low income workers cannot afford to remain unemployed. Hence, poor quality employment rather than unemployment could be a more accurate indicator of labor disadvantage.

Housing conditions differ dramatically across neighborhoods. While in the wealthy municipality, 17.18% of houses have all home appliances (computer, radio, television, blender, telephone, fridge, hot water-heater, own car) in the poor county, only 8.22% of houses do. Interestingly, home ownership is high across the three municipalities; this tendency reflects the high proportion of self-constructed units that characterize Mexican municipalities, as is the case in most developing countries.

(Table 1 around here)

We used daily time series of air pollution, weather, and mortality data for Iztapalapa, Alvaro Obregon and Naucalpan de Juarez for the period 2001-2010 (see Figure 1). The air pollution and weather data were obtained from the monitoring system of air pollutants in the Mexico City Metropolitan Area-RAMA (from the Spanish, Red

Automatica de Monitoreo Atmosferico) which currently has 47 station located all over the Metropolitan Area, the station run 24 h during the 365 days of the year. Separated samples of particulate matter, based on a measurement of particles with an aerodynamics diameter less than or equal to $10\,\mu g/m^3$ (PM_{10}) and temperature were obtained for each municipality. The hourly measures were collapsed over 24-hour period to obtain a mean value for PM_{10} and ambient temperature. Daily numbers of deaths were obtained from the National Center of Health Statistics for the same time period. Deaths due to accidental and other external causes (International Classification of Disease) were excluded. Separate counts were also computed for deaths from respiratory mortality (International Classification of Diseases or ICD 10 causes J) and cardiovascular mortality (International Classification of Diseases or ICD 10 causes I).

(Figure1 around here)

3. Model

Understanding the number of the at-risk population will improve our understanding of the association between pollution and health. However, the number of susceptible cannot easily be observed. Our purpose is to plot the number of people in the at-risk population over time using observed mortality data; the basic idea for this approach was postulated by Murray and Nelson (2000). These authors takes as a given that a portion of the urban population is at-risk, subject to a probability of death, or hazard rate, that varies with atmospheric conditions including total suspended particulates. New entrants replenish the at-risk population over time. This at-risk population, new entrants, and the hazard rate are unobserved, but they can be estimated by applying the Kalman filter to the observed daily atmospheric conditions and mortality counts. Using the Kalman filter is possible to infer the hazard rate over time, its relationship to atmospheric variables, and the implied path of the unobserved at-risk population. In the state-space framework, one is also able to address the following questions: What is the size of the at-risk population? What is the life expectancy of individuals in that population? What is the effect of changes in air quality on that life expectancy?

Contrary to the classical Poisson regression model widely used on this kind of analysis, in the state-space model the impact of at risk factor such as PM_{10} on mortality is indirect; as it is shown below, it is proportional to the size of the at-risk population on that day which is not observed directly. If the at-risk population has been depleted by recent mortality, then the impact of at-risk factors will be mitigated since it is a temporarily smaller population that is at risk. Indeed, it is this harvesting effect which allows the unobserved at-risk population to be estimated by the Kalman filter. If a higher hazard rate persists, the mortality count will fall back towards its previous level, since in the long run mortality is limited to the rate of new arrivals. However, the life expectancy of those in the at-risk population will fall, and this alternative approach allows us estimations of that effect.

At the center of Murray and Nelson (2000) model is an unobserved at-risk population from which all no traumatic deaths are assumed to drive. This at-risk population is the subset of individuals whose survival is threatened for various reasons, even in the absence of environmental hazards. The basic idea of the model is that the at-risk population is depleted by deaths and replenished by the arrival of newly frail entrants. The model focuses on the frail who do not recover and scape from this frail status. The at-risk population on a given day is defined as its value on the previous day, plus new entrants, and minus deaths. A first order difference equation accounts for daily changes in the at-risk population in the following way

$$P_t = P_{t-1} + N_t - D_t \qquad (2)$$

where P_t is the unobserved at-risk population, N_t is the number of new arrivals, and D_t is the observed number of deaths, all on day *t*. Each member of the at-risk population faces a probability of death that is function of environmental conditions, including ambient air quality. Daily deaths are represented by the following equation

$$D_t = (\boldsymbol{\gamma}'\boldsymbol{x_t})P_{t-1} + e_t \qquad (3)$$

Environmental hazards $\boldsymbol{x_t}$ are present in a hazard function $\boldsymbol{\gamma' x_t}$ and determine the amount of the at risk pool that is depleted or replenished daily by environmental and seasonal factors. The hazard function is the daily probability of death and is assumed to be linear combination of atmospheric variables, including an intercept term. The correct hazard function is unknown, as it is in the Poisson regression model. This requires an exploration of various hazard functions, which will be referred as models. Deaths are also allowed to occur at random, as capture by the random error term e_t.

As in Murray and Nelson (2000) our baseline model use the following hazard function

$$\boldsymbol{\gamma' x_t} = \gamma_0 + \gamma_1 PM_{10}$$

in this model γ_0 is the constant probability of death in the absence of environmental effects, and γ_1 is the marginal effect of PM_{10} on mortality.

In the basic model of Murray and Nelson (2000), where the time series of mortality analyzed was stationary, new members of the at-risk population N_t were assumed to enter randomly with a constant mean N equal to the mean daily deaths, plus Gaussian errors. Given the high variability in the population growth rate on most of the MCMA municipalities, the time series of mortality counts that we analyze are non-stationary. Therefore, we depart from Murray and Nelson at this point assuming that new members of the at-risk population enters as follows

$$N_t = N_{t-1} + \eta_t \qquad (4)$$

Because the at-risk population P_t and the new entrants N_t are unobserved, the parameter of this dynamic model cannot be estimated by conventional methods. However, the unobserved components can be estimated by using the state-space technique. Casting the model in this form makes it possible to use the Kalman filter for parameter estimation. The representation consider equation (3) as a Measurement equation, that is

$$D_t = [0 \quad \gamma' x_t \quad 0] \begin{bmatrix} P_t \\ P_{t-1} \\ N_t \end{bmatrix} + e_t$$

Then, we write (2) and (4) as the following state equation

$$\begin{bmatrix} P_t \\ P_{t-1} \\ N_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} P_{t-1} \\ P_{t-2} \\ N_{t-1} \end{bmatrix} - \begin{bmatrix} D_t \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \eta_t$$

If errors terms are assumed to be normally distributed, then the parameters of the model can be estimated employing maximum likelihood technique. For instance, parameters estimates in the above system can be obtained by starting with an initial guess for the state vector and its covariance matrix. Given the initial estimated parameters, the Kalman filter recursively generates the prediction equation. Ultimately, the filter generates estimates of the unobserved components $\hat{P}_t$ and $\hat{N}_t$ as well as $\hat{\boldsymbol{\gamma}}$, $\hat{\sigma}_e$ and $\hat{\sigma}_\eta$. The mean life expectancy of subjects in the at-risk population is calculated as the reciprocal of the estimated mean hazard rate and the daily average at-risk population deaths is the ratio of the average mortality to the daily average at risk-population.

4. Results and discussion

Using Kalman Filters, we estimate the observation and state equation by maximum likelihood. Tables 2 to 7 reports the estimates and asymptotic standard errors of the five base line specifications of the risk function that include various combinations of PM_{10} and average temperature (*Avtem)*; the square of temperature, and the multiplicative interaction of PM_{10} with *Avtem.* A constant term is included in every risk function. Model 1 uses only PM_{10}. Model 2 adds *Avtem*. Model 3 adds the square of *Avtem* to allow for hazard rate that increases at both extremes of temperature. Model 4 is included for comparison purposes and uses only the *Avtem* variable. Finally, Model 5 allows the effect of PM_{10} and *Avtem* to each depend on the value of the other by adding the interaction variable *Avtem**PM_{10}. Estimates are produced using the Kalman smoother, which uses all information available in the sample, thus providing a better in sample fit compared with the basic Kalman filter, which only uses information available at time *t*.

Turning to the analysis of each one of the municipalities, Tables 2 and 3 shows that when comparing the log likelihood of Model 5 with that of Model 4, which does not include either PM_{10} related variable, the likelihood ratio test suggests that for non-accidental and cardiovascular-respiratory mortality causes; PM_{10} is highly significant in both populations. We can also observe that when comparing Model 5 with Model 1, which does not include either *Avtem* related variable, the likelihood ratio test suggests that *Avtem* is also highly significant in both populations. We also note that the interaction variable *Avtem**PM_{10} is not significant in Model 5, when we compare the log likelihood with that of Model 3, the likelihood ratio test suggests that Model 3 is preferable to Model 5. Thus, for Iztapalapa we regard Model 3 as a reasonable baseline specification in both, non-accidental and cardiovascular-respiratory deaths.

For non-accidental and cardiovascular-respiratory deaths, the hazards functions of Models 3 imply that both extremes of temperature are harmful and that PM_{10} is also harmful with the effect rising with temperature. At the average level of PM_{10} observed on the sample, the effect of an increase of temperature from the minimum (7°C) to the maximum (25°C) value observed in the sample is an increase of the hazard rate from 0.076 to 0.087 for the non-accidental, while for the cardiovascular-respiratory the increment is from 0.077 to 0.153. On the other hand, at the maximum temperature of 25°C, the effect of an increase of PM_{10} from the minimum ($7\ \mu g/m^3$) to the maximum ($268\ \mu g/m^3$) value observed in the sample is to rise the hazard rate from 0.085 to 0.097 for the non-accidental, while for the cardiovascular-respiratory the increment is from 0.150 to 0.165.

Figures 2 and 3 plot the Kalman filter estimates of the at risk populations along with the estimated hazards rates in Model 3. The estimated at-risk population average 247 for the non-accidental deaths, while average 144 for the cardiovascular-respiratory deaths and varies seasonally. Since average mortality is 20 and 7 per day, this implies that about 8% and 6.9 % of the at-risk population dies on average per day in the non-accidental and cardiovascular-respiratory populations, respectively. The hazards rates fluctuate seasonally as periods of high emission of PM_{10} and temperature extremes gather a grim harvest, followed by less lethal conditions. Historically data suggest that the highest PM_{10} concentration occur in the MCMA in late winter and early spring. We observe that the estimated at-risk population series does move higher with time, from an average of 216 in the early years to around 287 in the later years for the non-accidental deaths, while it moves from an average of 83 to around 123 in the same period for the cardiovascular-respiratory deaths. There is a corresponding and offsetting decline in the hazard rate, moving downwards from an average of about 0.082 to 0.081 for the non-accidental deaths, while it move downwards from 0.113 to 0.112 for the cardiovascular-respiratory deaths in the same period. This decline in the hazards rates is driven by a reduction of PM_{10} average emissions of about ($65\ \mu g/m^3$) to ($47\ \mu g/m^3$) during the early and later years, respectively, and suggests that air control strategies implemented by the government since 1990 contributed to maintaining PM_{10}under 24 h maximum limit and resulted in a decreasing trend during this period.

As pointed out by Murray and Nelson (2000), while an increase in risk factors cannot increase mortality in the long run, life expectancy is the inverse of the hazard rate, so hazard causing agents will shorten it. The hazard rates observed over the sample period goes from 0.075 to 0.096 for the non-accidental deaths, while it goes from 0.075 to 0.157 for the cardiovascular-respiratory deaths. Therefore, we have a life expectancy ranging from 10-13 days for the non-accidental population, while life expectancy ranges from 6-13 days for the frail population of cardiovascular-respiratory deaths.

(Table and Figure 2 around here)

(Table and Figure 3 around here)

Analogous to Iztapalapa´s selection model, we have that for Naucalpan de Juarez the likelihood ratio test suggests that model 5 is preferable for the non-accidental deaths, while model 3 is preferable for the cardiovascular-respiratory deaths

At the average level of PM_{10} observed on the sample, the effect of an increase of temperature from the minimum (5.44°C) to the maximum (25.82°C) value observed in the sample is an increase of the Naucalpan de Juarez´s hazard rate from 0.045 to 0.063 for the non-accidental, while for the cardiovascular-respiratory the increment is from 0.042 to 0.050. On the other hand, at the maximum temperature of 25.82°C, the effect of an increase of PM_{10} from the minimum ($6.33\ \mu g/m^3$) to the maximum ($137.27\ \mu g/m^3$) value observed in the sample is to rise the hazard rate from 0.051 to 0.093 for the non-accidental, while for the cardiovascular-respiratory the increment is from 0.050 to 0.052.

Figures 4 and 5 plots the Kalman filter estimates of the at-risk populations along with the estimated hazards rates in models 5 and 3, respectively. The estimated at risk population average 245 for the non-accidental deaths, while average 60 for the cardiovascular-respiratory deaths and varies seasonally. Since average mortality is 9.91 and 2.53 per day, this implies that about 4.0% and 3.3 % of the at-risk population dies on average per day in the non-accidental and cardiovascular-respiratory populations, respectively. As in Iztapalapa, the hazards rates fluctuate seasonally as periods of high emission of PM_{10} and temperature extremes gather a grim harvest, followed by less lethal conditions. We observe that the estimated at-risk population series does move higher with time, from an average of 232 in the early years to around 263 in the later years for the non-accidental deaths, while it moves from an average of 60 to around 70 in the same period for the cardiovascular-respiratory deaths. There is a corresponding and offsetting decline in the hazard rate, moving downwards from an average of about 0.040 to 0.039 for the non-accidental deaths, while it move downwards from 0.041 to 0.040 for the cardiovascular-respiratory deaths in the same period. This decline in the hazards rates is driven by a reduction of PM_{10} emissions of about ($47.16\ \mu g/m^3$) to ($43.90\ \mu g/m^3$) during the early and later years, respectively.

The hazard rates observed over the sample period goes from 0.037 to 0.046 for the non-accidental deaths, while it goes from 0.039 to 0.051 for the cardiovascular-respiratory deaths. Therefore, we have a life expectancy ranging from 21-27 days for the non-accidental deaths, while life expectancy ranges from 19-25 days for the frail population of cardiovascular-respiratory deaths.

We observe that having a small at-risk population in Iztapalapa and Naucalpan de Juarez, lead to clear mortality displacement as the number of deaths fell bellow the average seasonal pattern after a high risk event and did not return to the normal until November. We also observe that the at-risk population is most exhausted at the end of winter (the end of the risk period) and is most replenished at the middle of autumn (the end of the safest period).

(Table and Figure 4 around here)

(Table and Figure 5 around here)

Finally, in a similar way than for Iztapalapa and Naucalpan de Juarez, based on the likelihood ratio test results we regard Model 5 as a reasonable baseline specification in both, non-accidental and cardiovascular-respiratory deaths for Alvaro Obregon.

As in the previous two municipalities we explore how PM_{10} and temperatures affect Alvaro Obregon´s hazard rate. Our results shows that at the average level of PM_{10} observed on the sample, the effect of an increase of temperature from the minimum (5.80°C) to the maximum (23.94°C) value observed in the sample is an increase of the hazard rate from 0.0068 to 0.0069 for the non-accidental, while for the cardiovascular-respiratory the increment is from 0.0075 to 0.0076. On the other hand, at the maximum temperature of 23.94°C, the effect of an increase of PM_{10} from the minimum ($6.88\,\mu g/m^3$) to the maximum ($115.32\,\mu g/m^3$) value observed in the sample is to rise the hazard rate from 0.0059 to 0.0093 for the non-accidental, while for the cardiovascular-respiratory the increment is from 0.0043 to 0.0155.

Figures 6 and 7 plots the Kalman filter estimates of the at-risk populations along with the estimated hazards rates in model 5. We observe lower hazard rate with high variability compared with that of Iztapalapa which is higher with low variability. A lower hazard rate lengthens life expectancy and allows individuals to stay longer in the at-risk population, thereby making that population greater than the one of Iztapalapa and Naucalpan de Juarez. The estimated at-risk population average 1850 for the non-accidental deaths, while average 565 for the cardiovascular-respiratory deaths and vary seasonally. Since average mortality is 9.28 and 2.56 per days, this implies that about 0.48% and 0.35% of the at-risk population dies on average per day in the non-accidental and cardiovascular-respiratory deaths, respectively. The hazards rates fluctuate seasonally as periods of high temperature. As in the other two cases, we observe that the estimated at-risk population series does move higher with time, from an average of 1788 in the early years to around 1933 in the later years for the non-accidental deaths, while it moves from an average of 473 to around 644 in the same period for the cardiovascular-respiratory deaths. There is a corresponding and offsetting decline in the hazard rate, moving downwards from an average of about 0.0050 in the early years to 0.0049 in the later years for the non-accidental deaths, while it move downwards from 0.0045 in the early years to 0.0044 in the later years for the cardiovascular-respiratory deaths. This decline in the hazards rates is driven by a reduction of PM_{10} emissions of about ($35.93\,\mu g/m^3$) to ($35.68\,\mu g/m^3$) during the early and later years, respectively.

The hazard rates observed over the sample period goes from 0.0046 to 0.0063 for the non-accidental deaths, while it goes from 0.0038 to 0.0067 for the cardiovascular-respiratory deaths. Therefore, we have a life expectancy ranging from 158-217 days for the non-accidental deaths, while life expectancy ranges from 149-263 days for the frail population of cardiovascular-respiratory deaths.

The seasonal pattern in the at-risk population with low hazard rate is interesting. We observe that for a large at-risk population the number of deaths remained slightly below average for about two years. This longer term impact on deaths is reflected in the mean life expectancy per high risk event deaths of 13 and 27 days for the small at-risk population of Iztapalapa and Naucalpan de Juarez, respectively, while for the large at-risk population of Alvaro Obregon, the mean life expectancy is 217 days.

(Table and Figure 6 around here)

(Table and Figure 7 around here)

The results above show that major determinants of environmental health risk need to be considered when making assessments of risk and vulnerability in urban populations. Our findings suggest that the health risks related to air pollution are socioeconomically differentiated within and across municipalities. Our estimates show evidence that various aspects of social inequality contribute to the greater burden of environmental hazard exposure and health risk for the municipality with low socioeconomic status. Social inequality, such as residential segregation, may affect the options that communities have to address environmental and health problems. For example, poverty may affect the likelihood of having health insurance, low education reduces knowledges and life skills that allow people to gain more ready access to information and resources to promote health (Link and Phelan, 1995), high population density may influence transportation demand, as expressed through average daily vehicle-kilometers traveled in private motor vehicles per capita; in turn, changes in transportation demand influence total passengers vehicle emissions to which population are exposed.

These socioeconomic disparities between municipalities partially explain why we observe a lower hazard rate in the wealthy Alvaro Obregon compared to the higher hazard rate in the poor Iztapalapa. The lower Alvaro Obregon's hazard rate lengthens life expectancy and allows individuals to stay longer in the at-risk population, thereby making that population larger than the at-risk population of Iztapalapa whose individuals have lower life expectancy. This happened because the proposed state-space model assumed that all deaths must first be susceptible, so the smaller the at-risk population the grater the individual probability of death. This means that the smaller the at-risk population the sicker its average member, and hence the smaller the impact on long term mortality. These findings are consistent to what would be normally predicted by the environmental justice literature.

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Table 1. Environmental and socio-economic features of the study municipalities.

	Alvaro Obregon			Naucalpan de Juarez			Iztapalapa		
	Min.	Mean	Max.	Min.	Mean	Max.	Min.	Mean	Max.
PM_{10} (daily average in $\mu g/m^3$)	6.88	38.79	115.32	6.33	45.14	137.27	7.00	54.36	268.00
Daily average temperature (C)	5.80	16.30	23.94	5.44	16.24	25.82	7.00	16.70	25.00
Non Accidental Mortality	1.00	9.28	25.00	1.00	9.91	24.00	5.00	20.00	47.00
Cardiovascular and Respiratory Mortality	0.00	2.56	11.00	0.00	2.53	10.00	0.00	5.06	21.00
	2000	2005	2010	2000	2005	2010	2000	2005	2010
Population	687020	706567	727034	858711	821442	833779	1773343	182088	1815786
Poverty									
Per capita income (PPP USD)	14816	13651	20177	13583	14171	20112	10078	10481	16126
PWNM2S	43.07	33.24	23.64	47.11	38.72	28.02	50.29	38.82	36.04
GINI			0.442			0.454			0.409
Dwelling									
% All home appliance	17.18			16.01			8.22		
% Home ownership	63.06			60.07			57.15		
Socio-demographics									
PRM18BD	131.82	178.77	210.50	112.87	153.70	163.38	83.52	117.73	138.71
% People where the head-household is indigenous		2.20	2.35		5.20	6.00		3.90	4.11
Gender and household composition									
% Female labor force			3.14			3.67			3.80
% Female-headed household			29.38			24.87			29.00
Average person per household	4.15	3.87	3.68	4.18	3.94	3.82	4.33	4.09	3.91
Percentage of households with more than 7 members	5.89	4.40	3.46	5.45	4.10	3.45	6.81	5.39	4.31
Employment									
% Unemployment	1.76		4.43	1.37		4.51	1.66		5.05
% Informally employed			26.13			24.06			28.03
% Pop. Without public healthcare	47.12	40.57	30.03	44.79	43.56	41.60	51.31	50.51	38.30
Infant mortality rate (per thousand)	19.27	12.66	11.65	19.85	10.12	15.65	20.39	15.81	12.42

PWNM2S = Percentage of workers with at most 2 minimum salaries, PRM18BD = Population rate under 18 years with at least bachelor degree (Is a measure of the number of person in a county with at least bachelor degree per a 1000 individuals per year).

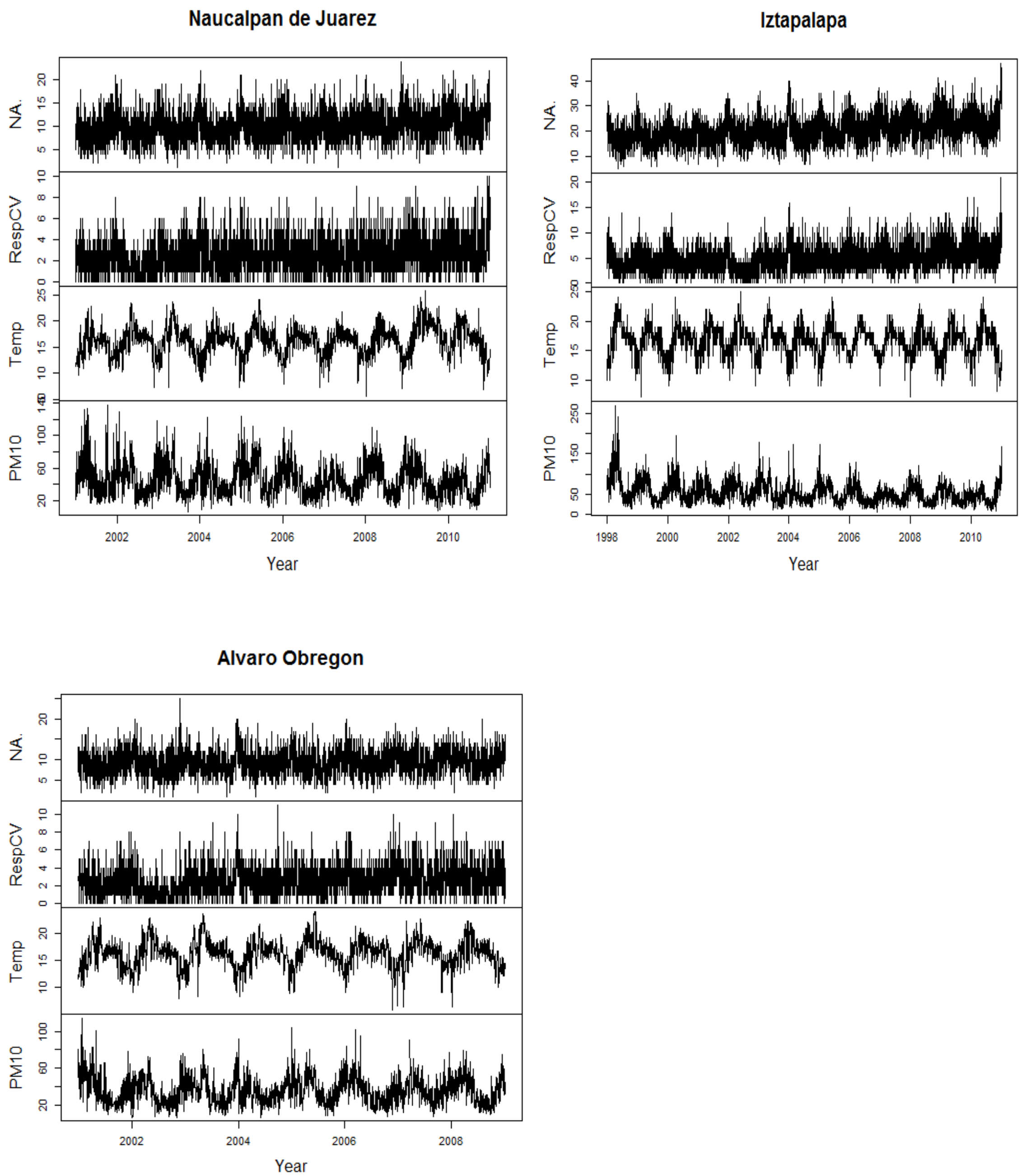

Figure 1. Daily time series of Non Accidental mortality (NA), Cardiovascular and Respiratory diseases (RespCV), Temperature (Temp), and levels of particulate matter with an aerodynamic diameter less than 10 $\mu g/m^3$ (PM_{10}) for Naucalpan de Juarez, Alvaro Obregon and Iztapalapa during the period 2001-2010. For Iztapalapa, data for the period 1988-2010 were used.

Table 2. Parameter estimates for Iztapalapa state-space models (standard errors in parenthesis). Non-accidental mortality counts

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
γ_0	0.0517673* (0.013920)	0.0711946* (0.015207)	0.0731026* (0.014924)	0.0813666* (0.016433)	0.0698405* (0.015839)
PM_{10}	0.0000428* (0.000015)	0.0000489* (0.000018)	0.0000471* (0.000017)		0.0000861 (0.000062)
$Avtem$		0.0006401** (0.000298)	0.0000330 (0.001020)	0.0001982 (0.001200)	-0.0000038 (0.000876)
$Avtem^2$			0.0000182 (0.000029)	0.0000209 (0.000035)	0.0000231 (0.000024)
$PM_{10} * Avtem$					-0.0000025 (0.000004)
σ_e	0.2863* (0.0527)	0.2585* (0.0354)	0.2597* (0.0358)	0.2583* (0.0301)	0.2612* (0.0375)
σ_η	19.5635* (0.4636)	19.0177* (0.4941)	19.0651* (0.5205)	18.9513* (0.4971)	19.1061* (0.5242)
$AVERISPO$	372	238	247	222	256
MLE(days)	15-19	10-12	10-13	10-12	11-13
DAVERISPD	5.3%	8.4%	8.0%	9%	7.8%
$\ln(L)$	-14060.123	-14055.217	-14055.064	-14059.057	-14054.914
Model selection test: Likelihood ratio test Model 5 vs Model 4: 8.28** Model 5 vs Model 1: 10.41** Model 5: vs Model 3: 0.30					

$Avtem$: Average temperature, *AVERISPO*: Average at risk-population, *MLE*: Mean life expectancy, *DAVERISPD*: Daily average at risk –population deaths. * ,**,** Significant at 1%,5%, and 10%

Figure 2. Iztapalapa´s estimated at risk population and hazard rate from model 3. Non-accidental mortality counts

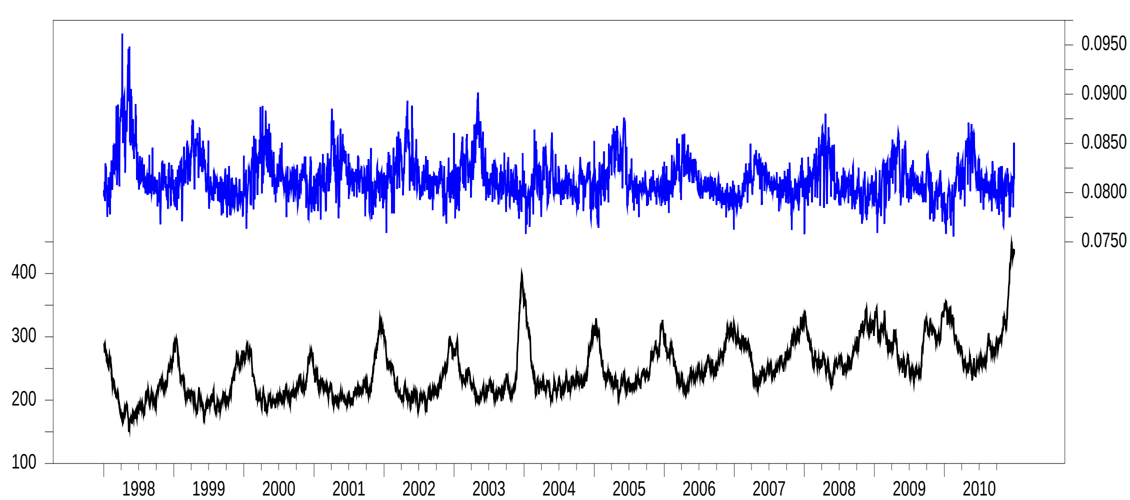

Table 3. Parameter estimates for Iztapalapa state-space models (standard errors in parenthesis). Cardiovascular-Respiratory mortality counts.

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
γ_0	0.0390000* (0.014156)	0.0478247* (0.014572)	0.0572752* (0.020528)	0.052562* (0.020113)	0.035773* (0.012902)
PM_{10}	0.0000599* (0.000022)	0.0000675** (0.000027)	0.000056** (0.000026)		0.0001829* (0.000067)
$Avtem$		0.0005804 (0.000373)	0.001874*** (0.001052)	0.002018 (0.001489)	-0.001452* (0.000524)
$Avtem^2$			0.000074*** (0.000042)	0.000091 (0.000049)	0.000069* (0.000026)
$PM_{10} * Avtem$					-0.000009 (0.000003)
σ_e	0.0493* (0.0105)	0.0464* (0.0075)	0.0477* (0.0100)	0.0465* (0.0075)	0.05285** (0.0145)
σ_η	5.0243* (0.1235)	4.9317* (0.1332)	4.9768* (0.1364)	4.9195* (0.1315)	5.0583* (0.1191)
$AVERISPO$	119	83	101	78	153
MLE(days)	18-25	12-18	6-13	12-16	25-34
DAVERISPD	5.8%	8.4%	6.9%	8.9%	4.5%
$\ln(L)$	-10779.983	-10777.679	-10774.915	-10779.770	-10773.693
Model selection test: Likelihood ratio test Model 5 vs Model 4: 12.15* Model 5 vs Model 1: 12.58* Model 5: vs Model 3: 2.44					

$Avtem$: Average temperature, *AVERISPO*: Average at risk-population, *MLE*: Mean life expectancy, *DAVERISPD*: Daily average at risk –population deaths. * ,**,** Significant at 1%,5%, and 10%

Figure 3. Iztapalapa´s estimated at risk population and hazard rate from model 3. Cardiovascular-Respiratory mortality counts.

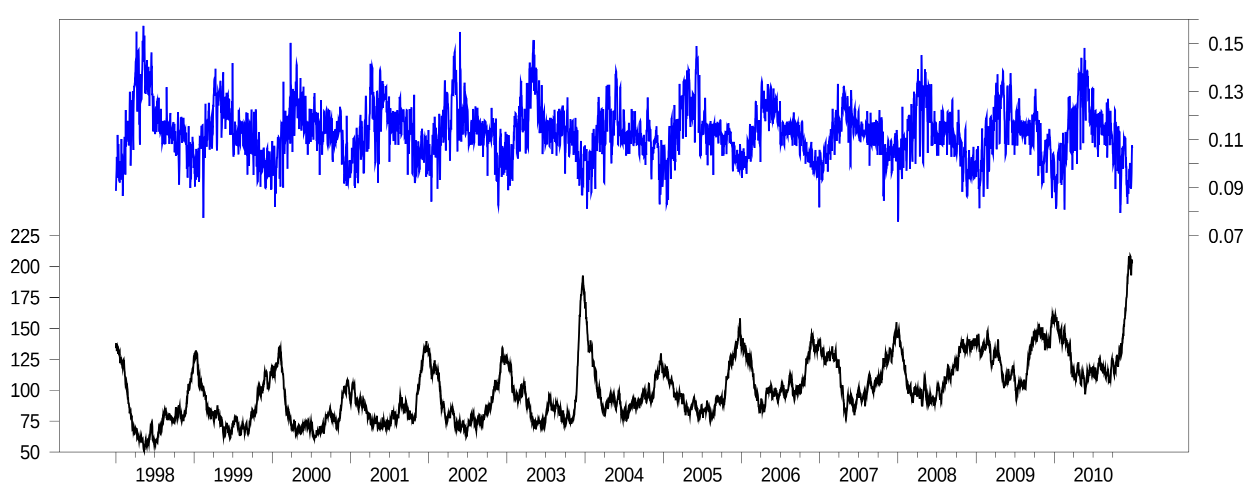

Table 4. Parameter estimates for Naucalpan de Juarez state-space models (standard errors in parenthesis). Non-accidental mortality counts

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
γ_0	0.0344581** (0.013759)	0.0424385* (0.000042)	0.0475469* (0.015814)	0.0497855* (0.014354)	0.0400705* (0.014322)
PM_{10}	0.000036*** (0.000019)	0.0000422*** (0.000023)	0.0000355*** (0.000021)		0.0001398** (0.00008)
$Avtem$		0.0002985 (0.000213)	-0.0008906 (0.000771)	-0.0010178 (0.000732)	-0.0007899 (0.000843)
$Avtem^2$			0.0000375 (0.000026)	0.0000437*** (0.000024)	0.0000445* (0.000027)
$PM_{10} * Avtem$					0.0000070* (0.000004)
σ_e	0.0547* (0.0140)	0.0525* (0.0111)	0.0528* (0.0117)	0.0536* (0.0118)	0.0522* (0.01179)
σ_η	9.7460* (0.2626)	9.6217* (0.2482)	9.6520* (0.2537)	9.6602* (0.2549)	9.6887* (0.2589)
$AVERISPO$	274	201	221	219	245
MLE(days)	25-32	19-22	19-23	19-23	21-27
DAVERISPD	3.6%	4.9%	4.5%	4.5%	4.0%
$\ln(L)$	-9466.406	-9464.690	-9463.463	-9465.930	-9461.233
Model selection test: Likelihood ratio test Model 5 vs Model 4: 9.39* Model 5 vs Model 1: 10.34** Model 5: vs Model 3: 4.46**					

$Avtem$: Average temperature, *AVERISPO*: Average at risk-population, *MLE*: Mean life expectancy, *DAVERISPD*: Daily average at risk –population deaths. * ,**,** Significant at 1%,5%, and 10%

Figure 4. Naucalpan de Juarez´s estimated at risk population and hazard rate from model 5. Non-accidental mortality counts

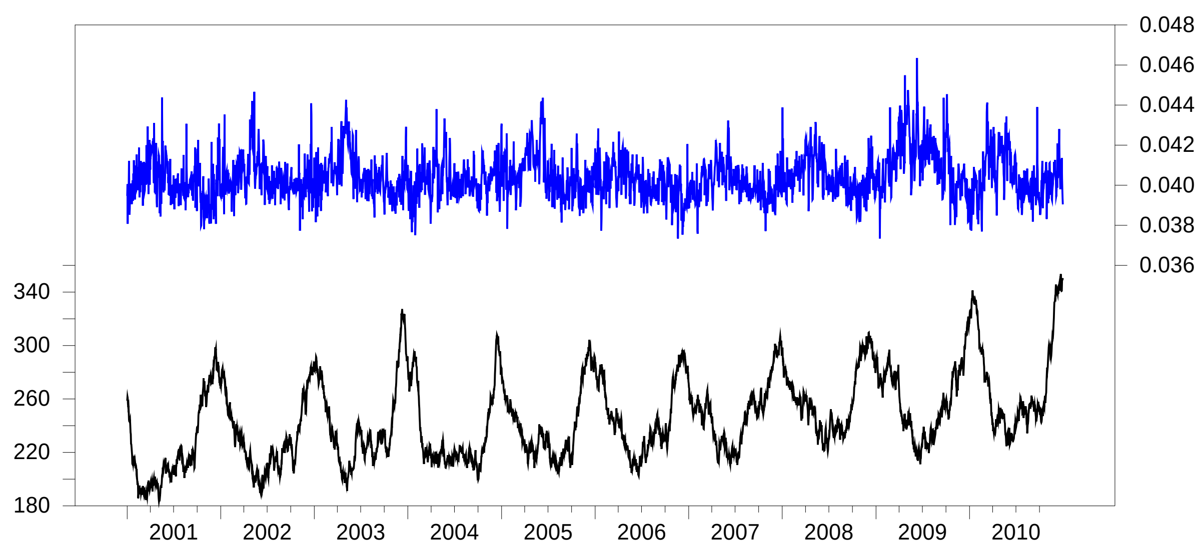

Table 5. Parameter estimates for Naucalpan de Juarez state-space models (standard errors in parenthesis). Cardiovascular-Respiratory mortality counts.

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
γ_0	0.0309206** (0.015591)	0.0352771* (0.011758)	0.0464546* (0.017443)	0.0481114* (0.018152)	0.0418381** (0.018547)
PM_{10}	0.0000232** (0.000012)	0.0000203*** (0.000015)	0.0000158 (0.000015)		0.0001117*** (0.000861)
$Avtem$		0.0003810*** (0.000279)	-0.0012113*** (0.000981)	-0.0012816 (0.001335)	-0.0011105 (0.001294)
$Avtem^2$			0.0000521*** (0.000030)	0.0000557*** (0.000043)	0.0000588 (0.000046)
$PM_{10} * Avtem$					-0.0000063 (0.000008)
σ_e	0.0096* (0.0028)	0.0093* (0.0020)	0.0093* (0.0022)	0.0092* (0.0021)	0.0092* (0.0020)
σ_η	2.4501* (0.0687)	2.4255* (.0525)	2.4263* (0.0643)	2.4250* (0.0643)	2.4293* (0.0649)
$AVERISPO$	79	59	60	59	63
MLE(days)	29-32	21-26	19-25	19-25	20-27
DAVERISPD	2.5%	3.3%	3.3%	3.3%	3.1%
$\ln(L)$	-6928.885	-6926.768	-6925.972	-6928.885	-6925.684
Model selection test: Likelihood ratio test Model 5 vs Model 4: 6.40** Model 5 vs Model 1: 6.56*** Model 5: vs Model 3: 0.57					

Avtem: Average temperature, *AVERISPO*: Average at risk-population, *MLE*: Mean life expectancy, *DAVERISPD*: Daily average at risk –population deaths. * ,**,** Significant at 1%,5%, and 10%

Figure 5. Naucalpan de Juarez´s estimated at risk population and hazard rate from model 3. Cardiovascular-Respiratory mortality counts.

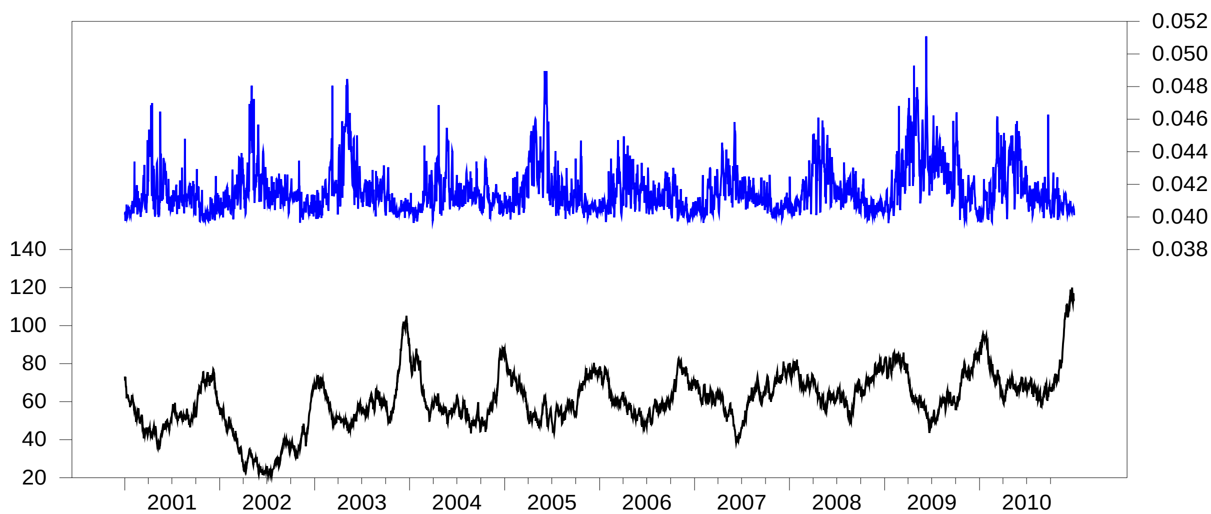

Table 6. Parameter estimates for Alvaro Obregon state-space models (standard errors in parenthesis). Non-accidental mortality counts

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
γ_0	0.0014023* (0.000359)	0.0071729 (0.005121)	0.0071047** (0.002813)	0.0022783* (0.016433)	0.0071041* (0.001885)
PM_{10}	0.0000019** (0.0000008)	0.0000163*** (0.000009)	0.0000093* (0.000003)		0.0000188* (0.000006)
$Avtem$		-0.0001000** (0.000042)	-0.0002715** (0.000134)	-0.0000928* (0.000032)	-0.0002405* (0.000039)
$Avtem^2$			0.0000066 (0.000004)	0.0000025** (0.000001)	0.0000077* (0.000001)
$PM_{10} * Avtem$					0.0000005* (0.0000002)
σ_e	3.4531* (0.0624)	0.0315* (0.0009)	0.1124* (0.0026)	2.1569* (0.0047)	0.1089* (0.0634)
σ_η	9.1451* (0.2511)	9.2280* (0.2687)	9.15710* (0.2483)	9.1676* (0.2369)	9.1528* (0.2361)
$AVERISPO$	6275	1501	1913	6371	1858
MLE(days)	625-714	128-185	166-227	55-714	158-217
DAVERISPD	0.14%	0.59%	0.47%	0.14%	0.48%
$\ln(L)$	-7429.322	-7423.335	-7422.738	-7425.923	-7419.444
Model selection test: Likelihood ratio test Model 5 vs Model 4:12.95* Model 5 vs Model 1: 19.75* Model 5: vs Model 3: 6.58***					

$Avtem$: Average temperature, *AVERISPO*: Average at risk-population, *MLE*: Mean life expectancy, *DAVERISPD*: Daily average at risk –population deaths. * ,**,** Significant at 1%,5%, and 10%

Figure 6 . Alvaro Obregon´s estimated at risk population and hazard rate from model 5. Non-accidental mortality counts

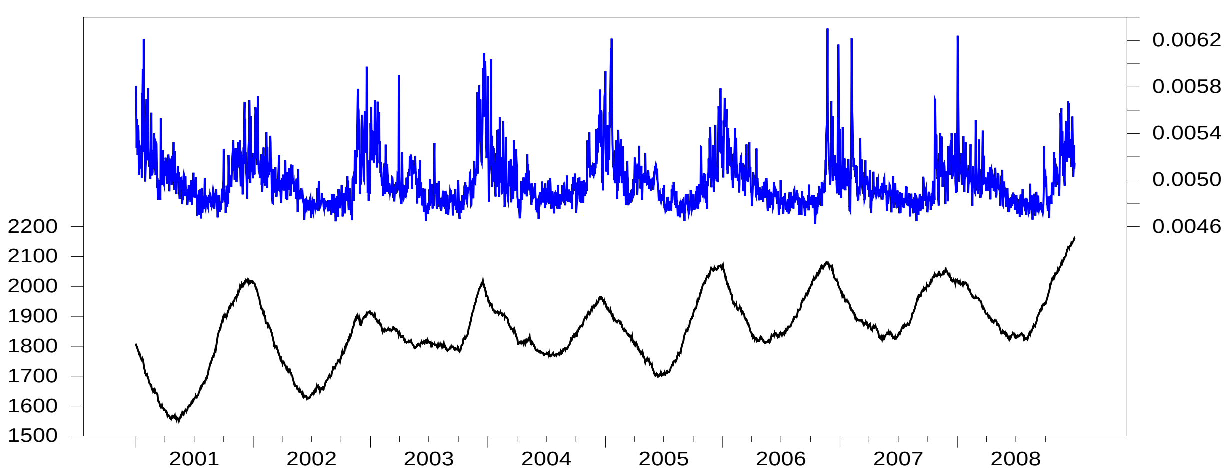

Table 7. Parameter estimates for Alvaro Obregon state-space models (standard errors in parenthesis). Cardiovascular-Respiratory mortality counts.

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
γ_0	0.0022922* (0.000502)	0.0019600* (0.000621)	0.0066468* (0.002375)	0.0124210* (0.003084)	0.0087584* (0.003251)
PM_{10}	0.0000065* (0.000001)	0.0000061** (0.000002)	0.0000123* (0.000004)		0.0000105 (0.000022)
$Avtem$		-0.0000413* (0.000013)	-0.0003802** (0.000174)	-0.0007212* (0.000238)	-0.0004931** (0.001294)
$Avtem^2$			0.0000093*** (0.000005)	0.0000200* (0.000007)	0.0000116 (0.000046)
$PM_{10} * Avtem$					0.0000039*** (0.000001)
σ_e	0.1590* (0.0040)	0.1258* (0.0029)	0.0293* (0.0004)	0.0260* (0.0003)	0.0183* (0.00007)
σ_η	2.5630* (0.0678)	2.5735* (0.0643)	2.5627* (0.0702)	2.5521* (0.0671)	2.5604* (0.0687)
$AVERISPO$	1007	1681	739	419	565
MLE(days)	333-434	476-833	193-334	112-164	149-263
DAVERISPD	0.19%	0.11%	0.27%	0.47%	0.35%
$\ln(L)$	-5563.340	-5554.896	-5553.908	-5558.009	-5552.023
Model selection test: Likelihood ratio test Model 5 vs Model 11.9** Model 5 vs Model 1: 22.63* Model 5: vs Model 3: 3.77***					

$Avtem$: Average temperature, *AVERISPO*: Average at risk-population, *MLE*: Mean life expectancy, *DAVERISPD*: Daily average at risk –population deaths. * ,**,** Significant at 1%,5%, and 10%

Figure 7. Alvaro Obregon´s estimated at risk population and hazard rate from model 5. Cardiovascular-Respiratory mortality counts.