

**Health impacts of environmental and  
socioeconomic factors on vulnerable groups  
in Mexico.**

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## Abstract

Environmental hazards and adverse socioeconomic conditions have negative impacts on people's health and are linked with both communicable and non-communicable diseases. Disproportionate exposure of vulnerable groups to environmental hazards can exacerbate environmental and health inequalities. Existing research has highlighted evidence of environmental and health inequalities, but gaps in understanding remain. This thesis addresses three areas of policy interest: the spatio-temporal dynamics of inequalities; the long-term impact of natural disasters on health inequalities; and the interaction between exposure to hazards and other determinants in affecting health outcomes. Using a multi-method, econometric approach that addresses spatial and temporal structure in the underlying datasets, I first analyse the distribution of air pollution in Mexico City. I show that the elderly and children, and neighborhoods with more deprived economic conditions, experience higher levels of air pollution compared with other age groups and neighborhoods. Second, I focus on how socioeconomic conditions affect health impacts in children, exploring the factors affecting the occurrence of low birth weight. My analysis shows hotspots of low birth weight across the greater Mexico City area and highlights lower education as a key risk factor. Finally, I examine health inequalities in vulnerable groups in relation to exposure to natural disasters such as floods and droughts across Mexico. My findings illustrate worsening morbidity and incapacity in children and the elderly following exposure to such events. This research has revealed new insights into the environmental and health inequalities experienced by vulnerable groups in relation to exposure to air pollution, natural disasters and adverse socioeconomic conditions. Policy action to reduce these inequalities requires the implementation of social programmes that focus on reinforcing community resilience after exposure to environmental hazards, regulating emissions of pollutants, monitoring adverse health outcomes, and extending public facilities and healthcare to the most vulnerable groups, especially children and the elderly.

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## Declaration

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as References.

Chapter 2, 3 and 4 have been written as scientific papers, which will be submitted to different Journals. Therefore, all the copyrights will be transferred to the respective publishers. Chapter 2 has been accepted as a paper in the XX Annual BIOECON Conference. It will be available on line in the following days. My Supervisors, Dr. Julia Touza-Montero and Professor Piran White, will be acknowledged as co-authors in the publications. In chapter three Dr Guangquan Li. will be added as co-author.

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Julia Touza-Montero and Piran White: Supervision, review and editing.

Guangquan Li: Statistical advice and editing in the chapter 3.



# Chapter 1: Health impacts of environmental and socioeconomic factors on vulnerable groups in Mexico.

## 1.1 Introduction

Environmental, social and economic factors play a significant role as determinants of health (Dahlgren & Whitehead, 1991; WHO, n.d. a). This thesis contributes to this area of research by investigating the impact of environmental and socioeconomic determinants on the health of vulnerable population groups in Mexico, a country with one the most unequal distribution of income in the world. Vulnerable groups explored include the economically disadvantaged segment of population, children, elderly and those with inadequate education. Children and elderly people are considered especially vulnerable. Children are particularly susceptible to health impacts because their immune system and organs are not properly developed (Menne et al., 2013; Kousky, 2016; Drisse & Goldizen, 2017). Elderly people are at risk of suffering adverse health outcomes because of their pre-existing health status, physical affections or physical limitations (Kovats & Kristie, 2006). In terms of environmental hazard to human health, this work focuses on air pollution in the city of Mexico, due to the elevated levels of pollution there that are well above the threshold established by World Health Organization (Air Quality in Mexico City, annual report, 2014). This thesis further examines environmental influences on health by considering the effects of natural disasters on morbidity and physical capacity. Although natural disasters are not specifically identified within the determinants of health framework, they are acquiring increasing research and policy attention due to their increasing frequency of occurrence and their negative consequences on public health in areas where they are more common (Baez & Santos, 2007; Vos et al., 2010; Guha-Sapir et al., 2014). Therefore, this thesis contributes to this incipient literature on the health impact of natural disasters. Mexico is a suitable area of study because its geographical position makes it prone to natural disasters (Rodriguez-Oreggia et al., 2013).

At the individual level, people with lower socioeconomic status (SES) are more likely to face elevated levels of pollution, and hence experience more negative impacts on their health, known as the ‘triple jeopardy’ (Jerrett et al., 2001). That is, different levels of exposure experienced by people with different socioeconomic backgrounds, either for air pollution or natural disasters, may affect their health differently, giving rise to *health inequalities*. In a similar way, the disproportionate exposure of vulnerable groups to

environmental hazards (also known as *environmental injustice or inequality*), may be linked with health inequalities. Given that people living in the same neighbourhood may have similar socioeconomic conditions and exposure to air pollution, the identification of spatial clusters where environmental injustice and health inequalities are most pronounced may also have important implications for policy.

The thesis comprises the following work. The second chapter explores environmental injustice in Mexico City, i.e., to what extent deprived economic and vulnerable age groups (children and elderly people) are exposed to either lower or upper levels of air pollution, PM<sub>10</sub> and ozone, in the city of Mexico. The third chapter investigates health inequalities with respect to the risk of term low birth weight (TLBW) in infants, by exploring income and education as key factors that can explain this health risk. This risk was chosen because it is widely recognised as an important indicator of children's health (Abrevaya & Dahl, 2008). The analysis also includes the spatial-temporal evolution of this health risk, exploring the dynamics of this risk in identified high, medium and low risk municipalities. The analysis is also done in Mexico City, but including the surrounding municipalities, covering an area known as Greater Mexico City. Lastly, the fourth chapter examines health inequalities with respect to the impact that recurrent and smaller-scale natural disasters may have on the health of vulnerable age groups (children and elderly). This is done by examining the consequences for morbidity and physical incapacity that may extend beyond the immediate impacts of these events.

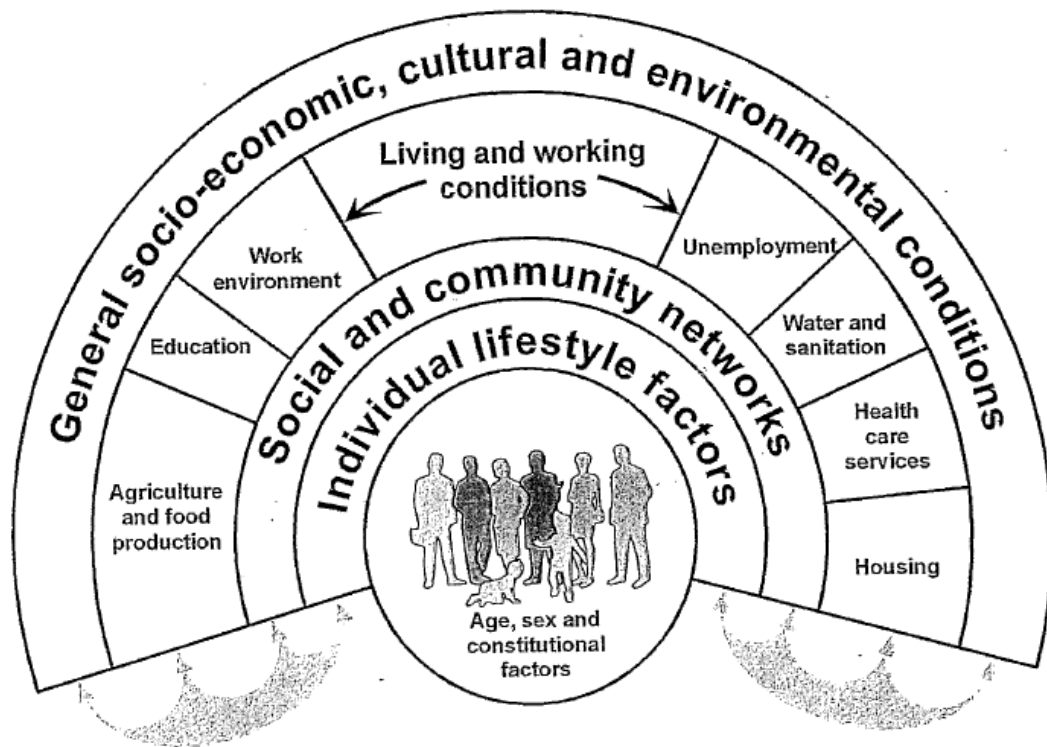
Given the negative impact of air pollution, natural disasters, and deprived socioeconomic conditions on the health of vulnerable groups (children, elderly people and people with lower socioeconomic status), this thesis provides key information that can contribute to policy making by addressing environmental and health inequalities, as for example, (i) air pollution programmes that can regulate emissions especially in the most affected areas identified in the thesis; (ii) social programmes that facilitate access to medical services and/or income support; (iii) policy programmes that can tackle the TLBW risk, particularly where this risk is increasing; and (iv) health programmes which monitor the trends of the adverse physical health outcomes of the most vulnerable social groups.

This introduction proceeds as follows. In the next section (1.2), the literature on the framework of health determinants is described. The following section (1.3) describes more in detail the existing evidence relating to socioeconomic determinants of health. The background on existing studies that examine the effect of environmental factors, air

pollution and natural disasters, on human health is presented in (1.4). Section 1.5 gives information about Mexico as study case. Finally, the last section (1.6) of this introduction contains the summary of the thesis and its structure.

## 1.2 Determinants of health framework

Health has been defined as a state of entire physical, mental and social well-being and not just the absence of any disease (WHO, 1948). There is strong evidence that social conditions influence health status (Rasanathan et al., 2010). The principal factors which give rise to health inequalities across social groups are originated from the circumstances in which people are born, grow, live, work and age (Marmot et al., 2008). These circumstances are known as social determinants of health and reflect social, economic, political, cultural, and environmental factors (WHO, n.d. a). There are two general frameworks of health determinants in the literature provided by WHO and Dahlgren and Whitehead (1991). For Dahlgren and Whitehead (1991) the health factors can be envisaged as series of interacting layers as illustrated in figure 1.1. The outermost layer represents a major structural environment which require political actions at national and international levels. Examples of this structural layer are economic strategies, tax policies, trade and environmental agreements. This is followed by material and social conditions where people live and work. In this layer, there are aspects of living and working conditions such as housing, education, health care, agriculture (food and nutrition) and employment. The next layer is the social and community networks such as the support of family, friends, neighbours and local community; this layer is about the mutual support when people gather to strengthen their defence against health hazards. The final, innermost layer of this determinant of health framework represents the lifestyle factors of the individual, which refers to the individual's actions such as his/her diet, and habits such as smoking or drinking. Under this framework, note that age, sex and genetics are important aspects of health, but they are considered as fixed factors in the sense that they are not amenable to influence or change from external factors and people have little control of them.



**Figure 2.1:** Social determinants of health. Source: (Dahlgren & Whitehead, 1991).

For the World Health Organization (WHO, n.d. a), the concept of determinants of health comprises the following factors: social and economic environment, the physical environment, the person's individual characteristics and behaviours; alongside with income, social status, education, physical environment (safe water and clean air, healthy workplaces, safe houses, communities and roads all contribute to good health), social support networks (families, friends and communities), culture (customs, traditions, beliefs), genetics, personal behaviour, coping skills, health services and gender.

Note that both frameworks have common factors which influence people's health. For instance, the layer of 'material and social conditions' by Dahlgren and Whitehead (1991) is related with the factors of the social and economic environment, the physical environment, income, social status, education and health care given by WHO. Similarly, the 'social and community networks' layer in the framework of Dahlgren and Whitehead (1991) is similar to the health determinant of 'social support networks' in the WHO framework. According to the WHO framework, not all the determinants have the same effect on health. The most influential are those which cause stratification in the society, called structural determinants. Examples of this are income, discrimination (gender, ethnicity, disability), political and governance structures. These factors are responsible

for creating socioeconomic positions, power, prestige, etc. and therefore these are the root cause of inequalities on health (WHO, n.d. a).

### 1.3 Socioeconomic determinants and health

Earlier research has conclusively shown how socioeconomic status (SES) has different effects on a large variety of health outcomes and inequities (Elo, 2009; Robinette et al., 2017; Marmot et al., 2008). For instance, Marmot et al. (2008) illustrates that there is a link between income and health, the lower the income the worse the health. Also, lower levels of education are common on people with poor health. Meanwhile, low education is linked with poor health conditions. In a review of the literature, Elo (2009) concluded that individuals with higher socioeconomic conditions are more healthier than those with lower SES. Robinette et al. (2017) concluded that people residing in neighbourhoods with high income were less likely to develop problems in mental and physical health conditions in the United States. Children and elderly people are particularly affected by deprived economic status in their health. Children were considered those from 0 to 11 years old in chapter 2, and between 2 and 9 years old in chapter 4; and elderly those who are from 65 years old onwards. Socioeconomically disadvantaged children are more likely to develop health problems in their future life (Case et al., 2005; Reiss, 2013; Braveman & Gottlieb, 2014). Braveman and Gottlieb (2014) illustrated that children with low socioeconomic status often suffer emotional and psychological stressors such as family problems and instability. Meanwhile, for elderly people who require more constant access to medical facilities and treatments to maintain their health, those in an economically disadvantaged position are not able to get the appropriate medical treatment, making them more vulnerable to declines in their health (Blazer et al., 1995).

A range of measures has been used to capture socioeconomic status of people in the context of health and inequality. For example, in the US, socioeconomic status is related with income and education but also importantly with race and ethnicity (Williams & Collins, 1995; Brown, 2018). In Europe, occupation (Mackenbach et al., 2000; Marmot, 2004) income and education (Cambois et al., 2001) have been used as indicators of social and economic status. For instance, in a longitudinal study in England and Wales from 1971 to 2009, overall mortality rates were lower amongst those with greater educational attainment (Flanagan & McCartney, 2015). In Europe, educational attainment, by itself, has been used as a measure to capture SES of people in the context of health inequalities (Mackenbach et al., 2008; Flanagan & McCartney, 2015), and shows more consistent

relations with health outcomes than income and occupation. J. P. Smith (2007) has pointed out that income and occupation do not capture long term influences on health properly. In contrast, education that starts in early years of life is not altered by health impairments which frequently appear after the education is completed.

#### 1.4 Environmental determinants and health

Environmental factors, which include all the physical, chemical and biological factors which are external to any individual (WHO, n.d. b), have an important influence on health and development (WHO, n.d. c). Some environmental factors promote people's health such as green or blue spaces, low pollution with a favourable climate or geography, access to healthy food, services and businesses (N. R. Smith et al., 2015). However, other environmental determinants can have a negative impact on health. These include air and water quality, patterns of energy use, patterns of land use and urban design; all these factors were shown by (Prüss-Üstün & Corvalán, 2006) to influence global disease burden. Other environmental factors that have been linked to health hazards include proximity to landfills, incinerators and noise (Schoolman & Ma, 2012; Raddatz & Mennis, 2013; Laurian & Funderburg, 2014).

Among these environmental health hazards, air pollution is one of the major concerns, and it is the focus of chapter 2 in the thesis. The cost of air pollution on non-communicable diseases has been estimated at around 10% of the global gross domestic product (World Bank, n.d.). According to WHO (2016), a great number of people living in cities (90%) are exposed to levels of air pollution that are higher than the thresholds established by WHO. Among the different pollutants, PM<sub>10</sub> and ozone have been distinguished as having a particularly severe impact on health. PM<sub>10</sub> can cause heart disease, lung cancer, asthma, and acute lower respiratory infections, with more than 2 million people dying annually as a result of breathing tiny particles, present in indoor and outdoor air pollution (WHO, 2011). Ozone is positively associated with daily mortality levels (WHO, 2006), and can cause reduction of lung capacity and serious lung damage (Levy et al., 2001). Air pollution damages human health in general, but vulnerable groups are found to be the most affected due to their age or current existing health problems (WHO, 2006). A large body of evidence shows the damage of air pollution on health of vulnerable groups, including children and elderly people (Liao et al., 1999; Bobak, 2000; Martins et al., 2004; Schwartz, 2004). For example, Martins et al. (2004) concluded that for a 10 mg/m<sup>3</sup>

increase in PM<sub>10</sub>, the percentage increase in respiratory mortality was from 1.4% to 14.2% in elderly people.

In this thesis, health inequalities related to natural disasters are also explored. Hyndman and Hyndman (2006) define a natural disaster in broad terms when an event causes harm, loss of life, physical injury or other health impacts, damage to property and livelihoods, or other social, economic and environmental loss. Attending to Below et al. (2009), IFRC, (n.d.), and WHO (1992) a natural disaster happens when a society experiences an environmental perturbation at a level that exceeds its ability to deal with it. The WHO (1992, p.2) defines a disaster as ‘‘a severe disruption, ecological and psychological, which greatly exceeds the coping capacity of the affected community’’. In that sense, these definitions consider that the impact of the natural disaster depends on the vulnerability of the society (Lal et al., 2009), i.e. the characteristics of any system (society or community) that make it susceptible to the harming impact of a hazard (UNISDR, 2009). Hazards associated with natural disasters are most commonly linked with sudden-onset events such as storms, but longer-lasting hazards such as droughts and floods can have similar impacts (slow onset events). Moreover, the cumulative impact of multiple smaller-scale events can sometimes be as severe as single, larger ones (Pörtner, 2010; Datar et al., 2013). Within the context of this thesis, I therefore take a broad view of ‘natural disasters’ and include both faster-onset and slower-onset hazards (Lal et al., 2009) of varying size, but which share common features in that they are environmentally driven and have significant immediate or long-term health impacts.

Natural disasters cause multiple impacts on health and livelihoods and can be highly economically damaging. For instance, in 2009, there were over 10,000 human deaths and economic damage in excess of 41 billion USD due to 335 reported natural disasters (Vos et al., 2010). Vulnerable age groups are especially susceptible to the damaging impacts of natural disasters (Gaire et al., 2016; Labra et al., 2018). Gaire et al. (2016) examine the effect of floods on infant stunting between 2007 and 2010 in Nepal. They concluded that children lower than 3 years old were severely stunted by the experience of this flooding. Another study showed that elderly people were particularly affected in their physical health (hypertension, shingles, physical fatigue, muscle and bone pain, erythroderma, cancer) as a consequence of the impact of an earthquake in Chile in February 2010 (Labra et al., 2018).

## 1.5 Mexico as case of study

Mexico is considered a developing country with one of the lowest gross domestic products per capita among OECD countries (18,535 US/capita in 2016, being the OECD average 42,151 US/capita) and highest income inequality (Gini coefficient= 0.46; =1, completely inequality, 2017) in the OECD countries (OECD, 2018). Mexico presents challenging problems in the areas of public health, air pollution and natural disasters.

In terms of public health in Mexico, life expectancy and neonatal mortality are some of the major concerns (Ministry of Health in Mexico, 2002; OECD, 2017). According to the OECD, Mexico, alongside with Latvia, had the lowest life expectancy which is around 75 years, in the OECD countries in 2015; the average was 80.6 across OECD countries. Mexico has had the slowest increase in life expectancy compared with the other OECD countries, since 2000 (OECD, 2017). There are different factors which explain the low life expectancy and the poor progress to increase it, such as poor nutrition, high mortality from circulatory diseases and limited access to good medical facilities (due to low levels of investment in the health sector). The spending in health care is four times lower than the average spending for OECD countries (OECD, 2017) which is a concern in the public health sector. With respect to neonatal mortality (where low birth weight is one of the principal factors) six in every 10 infant deaths (around 26, 400) occur in the neonatal period, but 45% of these deaths could be avoided with proper medical intervention (Ministry of Health in Mexico, 2008).

Air pollution is another major public concern in Mexico, especially in Mexico City. Mexico City is one of the most populated cities in the world; it comprises 16 municipalities with a population of 8,851,080 (7.8% of the total Mexican population) in 2010, and with a land area of 1,485 square kilometers. Mexico City is in the Valley of Mexico (Valle de México), a large valley in the high plateaus in the centre of Mexico. It is considered the most important city in Mexico in terms of the economy; it produced 17.07% of the country's gross domestic product (at constant prices of 2008) in 2012, according to the Mexican National Institute of Statistics and Geography (INEGI, 2014). The concentration of air pollution in Mexico City is affected by a number of factors: it has less oxygen (around 23% less than sea level) due to its high altitude; the stagnation of the air due to the U-shaped valley location; low thermal inversions especially in the



winter season; and plentiful solar radiation which increases the photochemical processes linked with some pollutants (Air Quality in Mexico City, annual report; 2014).

The principal sources of air pollution are from pollution emissions of industries and the transportation sector. Mexico City has been affected by the increase of both these sources. In the period 2008 to 2012 there was an increase in the vehicular fleet, close to 11%<sup>1</sup>, which is one of the major sources of pollution in Mexico City. The pollution of the air is related with high concentrations of PM<sub>10</sub>, ozone and PM<sub>2.5</sub>, according to the Mexico City Atmospheric Monitoring System (SIMAT, n.d.). Recently, Mexico City has reached elevated levels of pollution, PM<sub>10</sub> and ozone. The annual average PM<sub>10</sub> for 2014 and 2015 was 43.5 ug/m<sup>3</sup> (Air Quality in Mexico City, annual report 2014), and the concentration of ozone is also increasing, with an annual average of 27 and 29.5 parts per billion (ppb) in 2014 and 2015, respectively (Air Quality in Mexico City, annual report 2014). These figures are a concern because they are higher than the thresholds established by World Health Organization. According to the WHO, levels which are higher than these thresholds may trigger negative impacts on people's health. Air pollution has impacted both morbidity and mortality in Mexico. In 2010 there were 20,500 deaths due to the air pollution, with particulate matter being in the top ten of the riskiest health factors of mortality in Mexico (IHME, 2014). Air pollution has also had a large economic impact in Mexico, calculated as 3.4% of the Mexican GDP in 2012 (INEGI, 2014).

The geographical location of Mexico makes it prone to natural disasters (Rodriguez-Oreggia et al., 2013), which lead to severe economic loss, high rates of mortality and have negative impacts on people's health (Acosta & De la Parra, 2002; CENAPRE, n.d.). For instance, between 2000 to 2015 there were 2834 deaths and around 25.9 million people affected by natural disasters in Mexico, according to the National Centre of Disasters Prevention (CENAPRED)<sup>2</sup>. Among the different natural disasters registered in Mexico, floods and droughts are the most recurrent and characterized by high numbers of affected people (Rodriguez-Oreggia et al., 2013). In the period between 2000 and 2015, there were 126 and 145 records of floods and droughts respectively, with 776,296 and 950,820 of affected people respectively<sup>3</sup>. Some of the most recent and worst natural disasters in

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<sup>1</sup> It was elaborated based on the data Informe nacional de calidad del aire 2013, México, INEC-SEMARNAT and Cuarto almanaque de datos y tendencias de la calidad del aire en 20 ciudades mexicanas (2000:2009), Instituto Nacional de Ecología (INE), primera edición 2011.

<sup>2</sup> <https://datos.gob.mx/busca/dataset/impacto-socioeconomico-de-desastres-de-2000-a-2015/resource/868fe928-b3e7-4940-9e33-3abbb7cd41aa>

<sup>3</sup> Elaborated based on the data obtained in Centro Nacional de Prevención de Desastres (CENAPRED).

Mexico have been the hurricane Wilma in 2005, the floods in the state of Tabasco in 2007, the hurricanes Alex, Karl and Mathew in 2010, the tropical cyclones Ingrid and Manuel in 2013, and torrential rains (originating from the tropical storm Earl) in Puebla in 2016. Rains in Puebla caused an economic loss of 2,092 million of pesos. In 2016 a high proportion, 86%, of the total of economic loss (around 663 million of US dollars) was for hydrometeorological phenomena, of which 70.5% was due to strong rains and flooding; there were 135 registered deaths and more than 5 million people affected. The death toll due to natural disasters in 2016 was 135, which represents an increase of 14.4% over the numbers for 2015 (CENAPRED, 2016).

## 1.6 Summary of thesis aims and structure

This thesis aims to explore the health impacts of environmental and socioeconomic factors on vulnerable groups in Mexico. Chapter two and four investigate the burden of environmental factors (air pollution and natural disasters) on vulnerable groups. Chapter three analyses the impact of socio-economic determinants on child health, using low birth weight as an indicator of child health. The specific aims are:

- (i) To determine whether vulnerable groups (children, elderly and groups with economically-deprived conditions) are facing a disproportionate burden of air pollution (chapter two).
- (ii) To identify the evolution of areas (municipalities) with different levels of risk of having a child with low birth weight and examine the socioeconomic factors which are associated with this risk (chapter three).
- (iii) To examine the negative consequences on the health, morbidity and physical incapacity of children and elderly people due to natural disasters (chapter four).

Chapter two explores to what extent the level of neighbourhood deprivation and the proportions of children and elderly people in neighbourhoods are exposed to higher levels (as opposed to lower levels) of air pollution, at the resolution of basic geostatistical urban

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areas (AGEBs), the smallest administrative units in Mexico. Previous studies (Chaix et al., 2006; Carrier et al., 2014; Clark et al., 2014) have showed that deprived conditions and vulnerable groups face unequal exposure to air pollution. However, few studies (Rissman et al., 2013; Chakraborti et al., 2017) have analysed the burden of higher levels of concentration of air pollution on these groups. The importance of exploring different levels of air pollution (especially the higher levels) is due to their differing negative effects on people's health (Maantay et al., 2009). Therefore, this chapter takes in account the different levels of air pollution (especially lower and higher concentrations) and its high level of clustering across the Mexico City. Therefore, spatial quantile regression is applied to control for the potential spatial heterogeneity of the pollutants (clustering) over the studied areas, and to explore all the different concentration levels of air pollution. This work has two major contributions. First, this research applies spatial quantile regression in order to investigate the effect of lower and upper quantiles of air pollution and, at the same time, take into account any spatial autocorrelation. Secondly, it explores the unequal exposure of air pollution of vulnerable groups in Mexico City. This is the first such study in Mexico City, with most previous work being focused on the US, Canada and Europe.

Chapter three investigates the impact of socioeconomic conditions on infant low birth weight. Children with low birth weight are more susceptible to premature death and infectious diseases (Barker et al., 1993; Valsamakis et al., 2006). The understanding of the different risk levels of TLBW in different geographic areas over time is relevant for policy makers (Tu et al., 2012). Thus, this chapter models TLBW risk across Greater Mexico City, identifying the evolution of hot, cold and neither-hot-nor-cold spots accounting for spatial and temporal heterogeneity, and explores some possible socioeconomic factors associated with this risk. To model the variation in local geographical risk at the municipality level over time, I apply a Bayesian spatial-temporal approach, due to the disease data showing spatial and temporal structuring. The specific aims of this study are to: (a) Identify hot, cold and neither-hot-nor-cold spots of TLBW risk; (b) Identify the evolution of those municipalities that are existing hot spots and neither-hot-nor-cold spots that show a tendency to become 'hotter'; and (c) explain these space-time iterations using socioeconomic factors. This study therefore makes two contributions. First, while the analysis of space-time interaction (hot, cold and neither-hot-nor-cold spots) has been applied in the area of criminology (Li et al., 2014), using Bayesian methods; this is the first study to apply the technique to the study TBLW risk.

Secondly, this is the first time that such a study has been carried out in a large metropolitan area such as greater Mexico City.

The fourth chapter investigates the negative impacts on morbidity and physical incapacity of vulnerable groups (children and elderly) which have experienced natural disasters. There has been a significant increase in natural disasters with a clear negative impact on the health of vulnerable groups in the last decade (Baez & Santos, 2007; Guha-Sapir et al., 2014; Labra et al., 2018). Most of the evidence (Baez & Santos, 2007; Gaire et al., 2016; Labra et al., 2018) has focused on single natural disasters such as hurricanes, earthquakes and tsunamis. However, it is also important to explore recurrent and smaller-scale events due to their cumulative impacts on health (Pörtner, 2010; Datar et al., 2013). This chapter therefore examines the impact of natural disasters on morbidity and physical incapacity of children and elderly people in Mexico. I apply zero-inflated binomial modelling to adjust for the considerable number of zeros and overdispersion in the data set. This study contributes to the literature in two ways. First, it investigates how elderly people's health is affected by recurrent and different natural disasters, and second, it is the first such analysis in Mexico.

The final chapter provides a contextual view of the overall findings regarding the impact on the health of vulnerable groups, children and elderly, due to deprived economic conditions and environmental factors (air pollution and natural disasters). Based on this evidence, I illustrate how each group is affected by these factors and provide some policy recommendations and suggested areas for future work.

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## Chapter 2: Environmental Injustice in Mexico City: a spatial-quantile approach

### 2.1 Abstract

The majority of studies on environmental justice show that groups with lower socio-economic status are more likely to face higher levels of air pollution. Most of these studies have assumed simple, linear associations between pollution and deprived groups. However, empirical evidence suggests that health impacts are greater at high pollution concentrations. In this paper, I investigate the associations of extreme levels of particulate matter up to 10 micrometres in size (PM10) and ozone with deprived conditions, children and elderly people at sub-municipal level in Mexico City, using *Áreas Geoestadísticas Básicas* (AGEBs) as the unit of analysis. I used spatial quantile regression to analyse the association for each quantile of the range of pollution values, while also addressing spatial autocorrelation issues. Across AGEBs, higher levels of PM10 are significantly positively associated with deprived economic conditions and more elderly people. These results demonstrate clear variations in the associations between PM10 and vulnerable groups across the ranges of these pollutants. Ozone levels are positively associated with higher numbers of children. The findings reflect differences in the source and degradation of these pollutants and provide important evidence for decision-makers addressing air pollution inequalities and injustice in Mexico City and other cities.

Keywords: environmental inequality; air pollution; quantile analysis; socio-economic conditions; vulnerable groups.

### 2.2 Introduction

Environmental injustice refers to the unequal impact of environmental degradation on social groups depending on their social, economic, racial and ethnic background (Zimmerman, 1993; Pulido, 1996; Mohai et al., 2009; Raddatz & Mennis, 2013; Laurian & Funderburg, 2014). Evidence has been accumulating on the unequal distribution of environmental risk across social groups, with people of low SES living in close proximity to hazardous facilities (Zimmerman, 1993; Krieg, 1995; Pastor et al., 2001; Saha & Mohai, 2005; Mohai & Saha, 2007; Schoolman & Ma, 2012; Raddatz & Mennis, 2013), and incinerators (Laurian & Funderburg, 2014), having fewer green areas nearby (Johnson-Gaither, 2011; Wolch et al., 2014), living in areas with a high risk of flooding

(Grineski et al., 2015a), and being exposed to air pollution (Berry, 1977; Asch & Seneca, 1978; Grineski et al., 2007; Downey & Hawkins, 2008; Havard et al., 2009). However, other studies have not found environmental injustice (Hajat et al., 2013; Richardson et al., 2013; Padilla et al., 2014). The mixed nature of this evidence may be explained by differences in the type of hazard, geographical unit, methodology and local context (Briggs et al., 2008; Havard et al., 2009). This study focus on air pollution, where again, there are studies showing that people with lower socio-economic status are more exposed to air pollution (Grineski et al., 2007; Bell & Ebisu, 2012; Carrier et al., 2014; Clark et al., 2014; Zou et al., 2014), while other studies debate whether such links exist (Branis & Linhartova, 2012; Hajat et al., 2013; Richardson et al., 2013; Padilla et al., 2014). This literature emphasises the importance of targeting heterogeneous environments in policy making. This paper aims to investigate spatial heterogeneity in the relationship between air pollution and social vulnerability in the urban setting of Mexico City, in order to provide further information that could facilitate the improved targeting of local policies to mitigate or adapt to pollution threats. Spatially targeted environmental programmes potentially have the advantage of focusing on small areas, where policy measures can have a higher impact, particularly for the most vulnerable groups, than is the case when public resources are dissipated across the city. Moreover, local programmes may increase confidence and capacity to incentivise community participation in policy initiatives (Smith, 1999; Tunstall & Lupton, 2003).

The analysis will focus on PM<sub>10</sub> and ozone, because of the serious impacts on human health at high levels of these pollutants (Maantay et al., 2009), which highlight the need to better understand where the social heterogeneity in exposure to air pollution may occur. PM<sub>10</sub> can cause heart disease, lung cancer, asthma, and acute lower respiratory infections, with more than 2 million people dying annually because of breathing tiny particles, present in indoor and outdoor air pollution (World Health Organization, 2011). Ozone is positively associated with daily mortality levels (World Health Organization, 2006), and can cause reduction of lung capacity and serious lung damage (Levy et al., 2001). Moreover, Arceo et al. (2016) estimated that 1 µg/m<sup>3</sup> increase of in 24-hour PM<sub>10</sub> in my study area, Mexico City, results in an additional 0.24 deaths per 100,000 births. Thus, disproportional exposure of air pollution is strongly linked with health inequalities. Jerrett et al. (2001) defined this as ‘triple jeopardy’; people with deprived economic and social conditions are more likely to be exposed to high levels of contaminants and hence

experience more negative impacts on their health. As a result, air pollution is a concern at the public health level due to its detrimental impact on human health and on the economy (Lagercrantz & Sundell, 2000; Schwartz & Repetto, 2000; Jerrett et al., 2004; Maantay et al., 2009; Nishimura et al., 2013; Parent et al., 2013; Beatty & Shimshack, 2014). Hanna and Oliva (2015) estimated some of the economic costs of air pollution in Mexico City, showing that a 20% increase in air pollution can result in a reduction of 1.3 working hours in the following week. Filipine and Martinez-Cruz (Filippini & Martínez-Cruz, 2016) found that the individual's willingness to pay for improved air quality in this city amounts to an average of US \$262 (2008 US dollars) annually.

Here, I apply a quantile regression approach to investigate the hypothesis that the association between vulnerable groups and air pollution grows stronger as pollution concentrations increase. That is, in highly-polluted locations, I expect the evidence for environmental injustice to be stronger than in locations with lower levels of pollution. I therefore extend the work of Chakraborti et al. (2017) and Rissman et al. (2013), with the latter authors showing that higher airport-contributed PM<sub>2.5</sub> concentrations have different relationships with social minority indicators compared with the rest of the PM<sub>2.5</sub> distribution. My approach contrasts with most empirical studies, which explore the association between socio-economic conditions and air pollution assuming a homogeneous air pollution pattern across the studied area, using mean levels of air pollution with standard regression (i.e., ordinary least squares regression, OLS), leaving aside its lower and upper values with respect to the mean. The use of quantile regression, examining different percentiles of the conditional air pollutant distribution, can better account for spatial heterogeneity in air pollution levels and identify changes in its relationship with deprived economic conditions, that may be missed by the application of conventional mean regressions. It can hence be more informative to policy-makers. Programmes that mitigate air pollution impose social consequences associated with compliance with new regulations, as well as health benefits; the greater insights from quantile regression can help to identify any distributional issues that may need addressing in spatially targeted policies. In this sense, it is of interest to analyse the sensitivity of the environmental justice hypothesis (i.e. differences in vulnerable groups' exposures) at locations with extreme values of pollutants, as this may be the result of particular actions in these locations that do not necessarily occur elsewhere (e.g. the location of industrial facilities near age-vulnerable communities). In that case, policy makers can consider

spatially targeted emission-reduction policies (e.g. truck-rerouting, low-emission zones, industry re-allocation) in some locations to produce the strongest benefits to environmental justice (Nguyen & Marshall, 2018).

This research takes the sub-municipality *Áreas Geoestadísticas Básicas* (AGEBs), the smallest administrative units in Mexico, as the spatial unit of analysis. This has the advantage that socio-economic characteristics are likely to be fairly homogeneous within these small geographical areas, which will enhance the reliability of results obtained (Bowen et al., 1995; Maantay, 2002). Potential spatial autocorrelation will be accounted for in order to ensure robust hypothesis testing and the estimation of coefficients. Otherwise, the assumptions regarding the independence and identical distribution of the residuals would not meet. This may bias the estimators due to the inflated values of *t* statistics, and hence to reject the null hypothesis incorrectly, Type error I results (Anselin, 2002; Dormann et al., 2007). That is, the estimators would appear significant when they are not.

## 2.3 Data and Methods

### 2.3.1 Area of study

The choice of the case study of Mexico City is consistent with growing concerns about air pollution in urban areas in developing countries, where high population densities and low-quality health services collide with high levels of harmful pollutant concentrations, impacting on residents' health and well-being (Krzyzanowski et al., 2014; Marlier et al., 2016). In Mexico City, the annual average PM<sub>10</sub> for 2014 and 2015 was 43.5 ug/m<sup>3</sup>, and the concentration of ozone is increasing, with an annual average of 27 and 29.5 parts per billion (ppb) in 2014 and 2015 respectively (Air Quality in Mexico City, 2014). These values are higher than the World Health Organization (World Health Organization, 2006) thresholds, above which there are significantly increased risks to health. Moreover, there is also limited literature on environmental justice in developing countries (Pearce & Kingham, 2008; Rooney et al., 2012). For the specific case of Mexico, there is only scant evidence around environmental injustice, which is focused on industrial contaminants in the north and border regions with US, and with emissions generally obtained by measures of proximity to industrial facilities (Blackman et al., 2003; Grineski & Collins, 2008; Lara-Valencia et al., 2009; Grineski & Collins, 2010; Grineski et al., 2015b; Chakraborti et al., 2017). Chakraborti et al. (2017) provide an exception, as they undertook a nationwide analysis focusing on water disposal of toxic metals. They found a positive

association between marginalisation (poorer communities) and pollution, with stronger evidence at locations with higher levels of water toxic pollutants.

### 2.3.2 Pollution data

The pollution data, ozone and PM<sub>10</sub> for the year 2015, were obtained from the measuring stations operated by the Automatic Air Quality Monitoring Network of Mexico City (RAMA) (Automatic Air Quality Monitoring Network of Mexico City (RAMA), n.d.), which provide hourly records. I estimated the 24hr mean for PM<sub>10</sub> and ozone (from 10am to 6pm), each averaged into annual mean concentrations, following previous studies (e.g. (Romieu et al., 2012)). This analysis included data for all the stations that had at least 75% of information in the studied year. The numbers of measuring stations that met this criterion, and were therefore used to compute the 24hr values, were 23 and 31 available stations for PM<sub>10</sub> and ozone respectively. The geographical coverage of the monitoring stations network contains some areas with sparse data (see figure 2.A1a and 2.A1b on Appendix). The discussion further elaborates on this issue.

I applied a universal kriging algorithm to obtain interpolated values for each pollutant, at the AGEb level, from the monitoring stations data. This technique is considered one of the best interpolation methods because it deals better with erroneous local variability compared with other interpolation techniques such as inverse distance weight (IDW) (Jerrett et al., 2005a). I therefore complement previous work (Hanna & Oliva, 2015; Arceo et al., 2016) which has used the IDW technique to carry out the interpolation, leaving aside the spatial variability which is common in pollutant datasets. I chose universal instead of ordinary kriging because this approach considers the global trend over the area of study and takes into account the spatial dependence (Burrough & McDonnell, 1998). Moreover, universal kriging models have been used previously in the area of environmental justice along with epidemiological studies (Jerrett et al., 2001; Finkelstein et al., 2003; Künzli et al., 2005; Jerrett et al., 2005b; Su et al., 2011) to interpolate air pollution data.

### 2.3.3 Economic and geographic data

Economic information was obtained from the Population and Housing Census, INEGI, 2010 (INEGI, 2010) at the level of the AGEb, which includes the number of households with TV, car, computer, landline phone, mobile phone and internet; this information,



households' purchasing power, is used in this study to characterise the households' SES. Demographic information from the same data source was obtained on the number of children and elderly people. Children were considered those from 0 to 11 years old and elderly those who are from 65 years old onwards. Those AGEBS for which this information was either not available or labelled in the dataset as confidential ( $n = 126$ ) were excluded from the analysis, resulting in a total of 2,287 AGEBS in the analysis. Interpolated pollution and economic-geographic datasets were merged, assigning a pollutant value to each of the economic-demographic variable at the AGEBS level.

#### 2.3.4 Statistical analysis

A principal component analysis was used to generate a deprivation index as a proxy for households' economic deprivation conditions. This approach follows previous literature, where the method has been used to create socio-economic indices (Richardson et al., 2013; Rissman et al., 2013; Grineski et al., 2015a), particularly in a developing country context, due to a frequent lack of official data on income e.g. (Fiadzo et al., 2001; Fotso & Kuate-Defo, 2005). A principal component analysis also controls for the high collinearity among the economic variables. This analysis identifies the components which explain a significant cumulative proportion of the variance of the data set; I extracted the components with Varimax rotation to simplify the expression and hence its interpretation.

A Global Moran Index (Anselin et al., 1996) was calculated to explore the spatial distribution of  $PM_{10}$ , ozone (the original values from the monitoring stations and the interpolated values), deprivation index and vulnerable-aged groups. This index takes values from -1 to 1, where a large negative or positive value means that there is spatial autocorrelation, there are some clusters, where the values of the neighbouring AGEBS are dissimilar or similar respectively. In contrast, when the value approaches zero, it means that there is random spatial pattern.

As an initial exploratory analysis to assess environmental injustice, I assigned the annual averages of  $PM_{10}$  and ozone into five economic deprivation categories (quintiles) across Mexico City's AGEBS and used one-way ANOVA and Tukey-Kramer test to evaluate whether there were any statistical differences in the mean pollution levels for the extreme quintiles (i.e., between AGEBS with households with the lower and higher levels of deprivation conditions). I then use regression analysis, as done in previous studies

(Rissman et al., 2013; Carrier et al., 2014; Fecht et al., 2015) to assess the association of a given minority group with each pollutant, and determine its statistical significance, after controlling for the other groups. I first carried out standard OLS regressions to quantify general associations of economic deprivation and vulnerable-aged groups with PM<sub>10</sub> and ozone concentrations. I also analysed the potential heteroscedasticity, in terms of different variance of the residuals across the distribution, of the regression with the Breusch and Pagan (1979) test. To better understand exposure to high pollutant levels, and to deal with the potential heteroscedasticity, I applied a quantile regression. This simple technique allowed me to assess the levels of association of the economic deprivation index and the proportion of children and elderly people with concentrations of PM<sub>10</sub> and ozone across the full range of concentration levels for each pollutant. This allowed me to examine how the relationship of pollution levels for vulnerable groups changes at different levels of the pollutants (for example at the highest and lowest pollution levels). The presence of residual spatial autocorrelation was examined using the Moran Index for the analysis of both PM<sub>10</sub> and ozone, which led to evidence of the potential biased estimators; therefore, a spatial regression was applied in the quantile analysis to obtain accurate coefficients.

Briefly, I describe below the quantile regression which estimates the conditional quantile functions in contrast with the conditional mean functions of ordinary least square (OLS). Quantile regression uses the full sample and allows us to determine the effect of the determinants across the full distribution (quantiles) of the dependent variable. Unlike OLS, the quantile approach can deal with heteroscedasticity, outliers and unobserved heterogeneity (Koenker & Hallock, 2001; Koenker, 2005); in this analysis, this is convenient because it does not assume any distributional assumption (independent and identically distributed) of the residuals, allowing uneven distribution on the PM<sub>10</sub> and ozone. According to Koenker (2005) instead of minimizing the sum of the squared residuals as in OLS, quantile regression focuses on minimizing a weighted sum of the absolute deviations:

$$\min_{\{\beta_j\}_{j=0}^k} \sum_{i=1}^n |y_i - \sum_{j=0}^k \beta_j X_{j,i}| h_i$$

where  $y$  = dependent variable,  $X$  is the vector of the covariates and  $\beta$  is the vector of the slopes. The weight is defined either as  $h_i = 2q$  when the residual for the  $i$ th observation is positive or as  $h_i = 2 - 2q$  if the residual is negative; and  $q \in (0,1)$  denotes the quantile of the dependent variable to be estimated.

Spatial autoregressive models (SAR), lag model and spatial error, are commonly used to tackle the potential spatial autocorrelation in linear regressions (Anselin & Arribas-Bel, 2013). In this paper, I applied the lag model approach due to the fact that the quantile analysis is not applicable to the spatial error model (Liao & Wang, 2012) and because the dependent variable is highly clustered, with nearby AGEBS tending to have similar levels of pollution. Following (McMillen, 2012), the quantile regression with spatial lag model is defined as:

$$y = \lambda(q)Wy + X\beta(q) + u$$

where  $W$  is the spatial weight matrix, which denotes the spatial relation between each value of  $y$  and its neighbours;  $\lambda(q)$  is the spatial lag parameter;  $u$  is the error term. The  $W$  (weighted matrix) was constructed to model the structure of the spatial lag component, as shown above, by using the first contiguity method. This method was chosen because the size of AGEBS is highly heterogeneous (with mean 0.317 and standard deviation 0.324 square kilometres); it involves creating regions with links if AGEB  $i$  and AGEB  $j$  share one or more boundary points. Three isolated AGEBS were excluded from analysis because they did not have any neighbour.

There are different methods to handle the spatial lag component in a quantile regression model. Kim and Muller (2004) introduce the Two Stage Quantile Regression (2SQR) which requires the estimation of two consecutive quantile regressions. In this paper, however, I used an Instrumental Quantile Regression (IVQR) (Chernozhukov and Hansen (2006), where the same quantile is used just in one stage leading to more robust results (McMillen, 2012). First, an instrumental variable is created for  $Wy$  from the predictive values of an OLS regression of  $Wy$  on a set of instruments  $Z$  ( $X$  and  $WX$ ). Then, a quantile regression is fitted (one regression for each  $\lambda$  value)  $y - \lambda Wy$  on  $X$  and  $\widehat{Wy}$ , using the created instrumental variable for  $Wy$  ( $\widehat{Wy}$ ). The estimated value of  $\lambda$  leads to

small coefficients (closest to zero) on  $\widehat{W}y$ . Having the values of  $\widehat{\lambda}$  a quantile regression  $y - \widehat{W}y$  on  $X$  is fitted to get the estimated values of  $\beta$ . It is expected that  $\widehat{W}y$  will be zero when the instruments are chosen properly (McMillen, 2012). I analysed the estimated spatial lag variable to illustrate the level of spatial autocorrelation. Finally, an analysis of variance was applied to test whether the spatial coefficients across the different quantiles on the pollutants are statistically different from one another (Koenker, 2006). The final dataset contained 2,287 observations. I used R program version 3.2.3 for the analysis.

## 2.4 Results

### 2.4.1 Descriptive analysis

Table 2.1 provides an overview of the descriptive statistics of the pollution, economic and demographic variables, of the households, in percentages (%) in Mexico City. More than half of the households lacked internet access (60%) or had no car access (53%). In addition, approximately a quarter of them did not have landline or mobile phone access (28% and 25%, respectively).

**Table 2.1**

Description and descriptive statistics of the pollution, and households' economic and demographic variables in percentages (%) in Mexico City.

Name	Variable description	Type of variable	Data source	Mean	Std. Dev.	Min	Max
	Particulate Matter 10		RAMA <sup>1</sup>		5.50	33.5	56.1
PM <sub>10</sub>	(ug/m3)	Environmental		42.6			
Ozone	Ozone ( ppb <sup>2</sup> )	Environmental	RAMA	56.8	4.60	44.2	65.7
	%		PHC INEGI				
H. no car	Households without car**	Economic	2010 <sup>3</sup>	0.53	0.16	0.05	0.89
	%		PHC INEGI				
	Households without		2010	0.51	0.17	0.05	0.94
H. no pc	computer**	Economic					
	%		PHC INEGI				
	Households without land		2010		0.12	0.01	0.98
H. no ll	line**	Economic		0.28			

	%		PHC INEGI				
	Households		2010				
	without			0.08	0.00	0.66	
	mobile						
H. no cel	phone**	Economic		0.25			
	%		PHC INEGI				
	Households		2010	0.60	0.18	0.06	0.98
H. no	without						
inter	internet**	Economic					
			PHC INEGI				
Children	% Children	Demographic	2010	0.19	0.07	0.02	0.43
			PHC INEGI				
Elderly	% Elderly	Demographic	2010	0.19	0.06	0.02	0.37

Notes: All the variables are at the AGEB level (in total 2,287) with a population mean of 3,799.8 and standard deviation of 2,179.

<sup>1</sup> RAMA means Automatic Air Quality Monitoring Network of Mexico City.

<sup>2</sup> parts per billion

<sup>3</sup> PHC INEGI 2010 means Population and Housing Census 2010, INEGI.

\*\*Includes private homes for the housing characteristics, classified as detached house, apartment building, house or room at home or neighbourhood and fourth roof and did not specify that kind of housing are captured (INEGI)

Table 2.2 shows the results of principal component analysis (PCA) capturing the households' economic deprivation conditions. It shows that the first component explains 89% of the cumulative in all collinear economic variables and its eigenvalue is greater than 1. This component comprises one cluster which describes the level of deprivation of car, computer, landline, mobile phone and internet for the households. All variables had high loading values which reflect the important contribution on this first component. I considered this as an economic deprivation index. Households in AGEBs with low values of this deprivation index had better purchasing power (in terms of the economic variables), while high values represent worse deprived conditions.

**Table 2.2**

Principal Component analysis (PCA) results with component loadings for the economic variables for Mexico city AGEBs.

Components	Eigenvalue	Proportion	Cumulative
Comp1	4.60	0.89	0.89
Comp2	0.24	0.04	0.94
Comp3	0.20	0.04	0.98
Comp4	0.08	0.01	0.99
Comp5	0.18	0.00	1
Variable	PC1	h2	
H. no car	0.93	0.87	

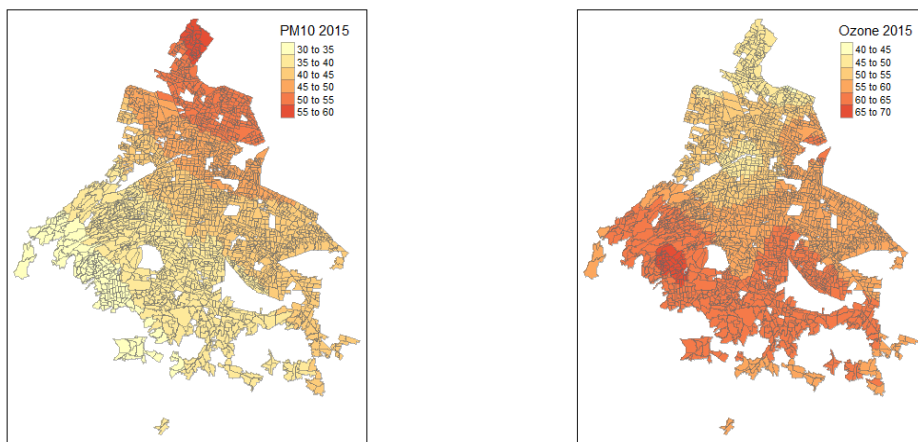
Varimax	H. no pc	0.99	0.98
rotated	H. no ll	0.92	0.84
component	H. no cel	0.90	0.81
matrix	H. no inter	0.98	0.96

The first component explains 89% of variance in all collinear independent variables.

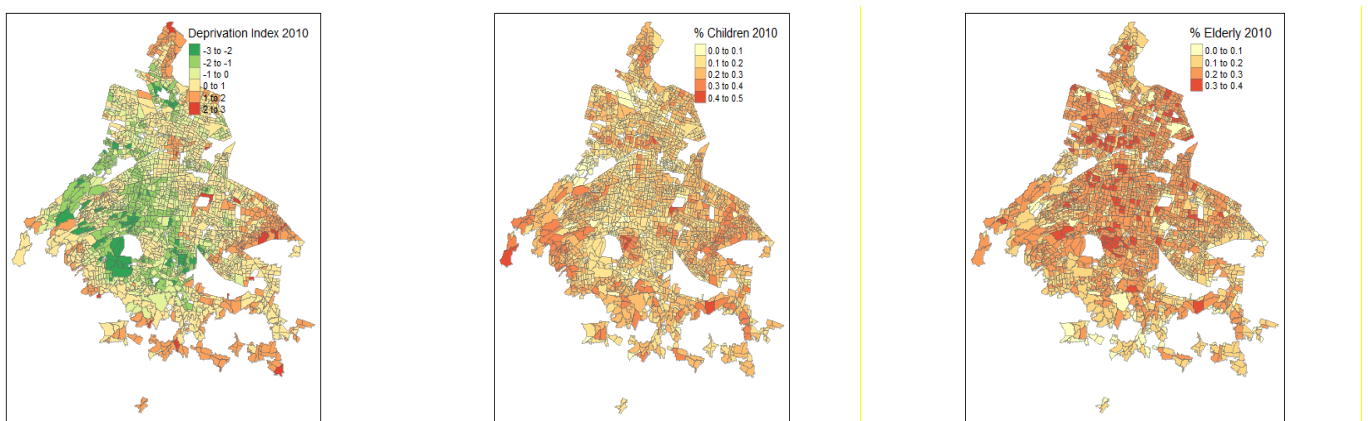
#### 2.4.2 Spatial analysis

An analysis on the potential spatial autocorrelation within the original pollutant dataset, coming from the monitoring stations, showed a positive and significant Global Moran Index [Moran Index=0.34 and 0.48 with a  $p$ -value<0.001] for PM<sub>10</sub> and ozone respectively. Similarly, the Moran index results for the interpolated pollution data also showed that there is a significant positive spatial autocorrelation in the concentration levels of both pollutants [Moran Index=0.99 with a  $p$ -value<0.001, for both pollutants]. Thus, Figures 2.1a and 2.1b show the spatial distribution of the PM<sub>10</sub> and ozone interpolated values, with a high level of clustering. These figures illustrate that the higher levels of PM<sub>10</sub> were mainly found in the north of the city, whereas the south faced lower levels. For ozone, it is the opposite: the south area presented higher levels of concentration, while in the north the levels were lower. These pollutants were thus found to be highly negatively correlated ( $r=-0.77$ , Pearson correlation), with a  $p$ -value<0.001. These different patterns reflect differences in the sources and chemical processes associated with particulate and ozone pollution. Particulate pollution is concentrated in cities due to its source in power generation, domestic heating and traffic. Ozone is not emitted directly into the city environment to any great extent but is formed through a series of photochemical reactions involving reactive organic compounds and nitrogen oxides emitted from combustion engines. However, the nitrous oxide (NO) produced from combustion engines also reacts with ozone itself to form nitrogen dioxide (NO<sub>2</sub>), thus removing ozone from the city environment. In suburban or peri urban areas (those areas which are on the edge of the city), there is less traffic, hence less available nitrous oxide to react with ozone, and ozone is therefore more persistent (Briggs et al., 2008; Fecht et al., 2015). Suburban or peri urban areas are common to the south of Mexico City, and hence there is greater ozone in this area. The spatial distribution of the economic deprived index in Figure 1c shows a relatively high level of clustering [Moran Index=0.7 with a  $p$ -value<0.001]. The distribution of the deprivation index shows an economic gradient from the less deprived AGEBS (green colour) to the most deprived AGEBS (red

colour). The AGEBs with the less deprived households form a big cluster located at centre-west, where the purchasing power is higher than in other locations in the city. Households with most deprived conditions form small clusters in the north, centre-east and south. Higher percentages of vulnerable groups (children and elderly people) are located in red coloured AGEBs. The Moran Indices for children and elderly people were 0.45 and 0.37, respectively, indicating the presence of statistically significant clustering of AGEBs with similar proportions of vulnerable age groups (with a  $p$ -value<0.001) (Figure 2.1d and 2.1e).



**Figure 2.1a and 2.1b:** Spatial distribution of PM<sub>10</sub> and ozone across Mexico City in 2015. Spatial units shown are AGEBs. The darker red shading shows the highest levels of concentration of PM<sub>10</sub> and ozone.



**Figure 2.1c, 2.1d and 2.1e:** Spatial distribution of deprivation index, proportion of children and elderly people across Mexico City in 2010. Spatial units shown are AGEBs. In Fig 1c) the red colour shows the areas with the more deprived conditions. In Fig 1d and 1e) the dark red and whiter colours show the areas with the higher and lowest proportion of children and elderly respectively.

Table 2.3 reports the descriptive statistics of PM<sub>10</sub> and ozone concentrations according to the quintiles of the deprivation index. The category q1 denotes the AGEBs with less economic deprivation conditions in terms of purchasing power and q5 captures those with the most deprived conditions. The results in this table show that the most economic deprived AGEBs (q5) experienced higher PM<sub>10</sub> concentration levels (43.3 ug/m<sup>3</sup>) compared with the less deprived AGEBs (q1), (40.3 ug/m<sup>3</sup>). In contrast, for ozone the most deprived AGEBs (q1) had lower concentrations (56.7 ppb) and the less deprived AGEBs (q5) had higher concentrations of this pollutant (57.4 ppb).

**Table 2.3:** Distribution of PM<sub>10</sub> and ozone concentrations levels by deprived index in quintiles, in ug/m<sup>3</sup> and ppb units respectively.

Category	PM <sub>10</sub>			Ozone		
	Mean	Min	Max	Mean	Min	Max
q1	40.30	34.40	53.90	57.4	48.40	65.70
q2	43.20	34.00	54.40	55.80	44.20	65.70
q3	43.30	33.70	54.20	56.70	45.30	65.70
q4	42.80	33.80	55.70	57.40	46.60	65.70
q5	43.30	33.50	56.10	56.70	44.90	65.30

Note: qi represents quintiles of the deprivation index, with q1 being the less and q5 being the most deprived AGEBs in terms of households' purchasing power.

I carried out one-way ANOVA and Tukey-Kramer tests to compare the differences in the mean values of both pollutants across the different deprived categories (i.e., across all the quintiles and between each quintile, respectively). One-way ANOVA shows that the means for all the quintiles were statistically different (with a *p*-value < 0.005) for both pollutants. The Tukey-Kramer test indicates that the differences for q1-q2, q1-3, q1-q4 and q1-q5 were significant (with a *p*-value < 0.005) for PM<sub>10</sub>. Similarly, the differences for q2-q1, q2-q3, q2-q4 and q2-q5 were also significant (with a *p*-value < 0.005) for ozone.

#### 2.4.3 Regression analysis

The regression analysis further assesses the relationship of pollution levels with the deprivation index, and the proportion of children and elderly. Table 2.4 illustrates the results of both OLS and the spatial quantile regressions, showing the relationship of PM<sub>10</sub> (table 4a) and ozone (table 4b), the economic deprivation index, percentage of children



and percentage of elderly people, at AGEB level. The heteroscedasticity identified in the OLS model [Breusch-Pagan with a p-value<0.001] and the positive spatial autocorrelation detected in the residuals of the quantile regression [Moran Index=>0.8 with a p value<0.001] justify the use of this spatial quantile regression. Both models in Table 4 show that the two pollutants were significantly related with the deprivation index and vulnerable-aged groups (p-value <0.001), but in different ways. In general, the analysis of the coefficients, for both models, shows that PM<sub>10</sub> (ozone) was positively (negatively) associated with economic deprivation conditions, after controlling for age groups. This provides evidence of environmental injustice for population with deprivation economic conditions residing in locations with higher PM<sub>10</sub> levels. In contrast, no such inequity was found for ozone; in fact, populations with lower deprivation conditions were associated with higher ozone exposure. Likewise, elderly people (children) were associated positively (negatively) with PM<sub>10</sub> concentrations, after controlling for SES conditions. In contrast, ozone levels were positively (negatively) associated with children (elderly).

**Table 2.4:** OLS and spatial quantile regression estimates assessing the relationship of (a) PM10 and (b) ozone and the economic deprivation index, children and elderly within each AGEB. Children and elderly are in percentages. The percentages (%) denote the different quantiles of the spatial quantile regression. All the estimators are significant with a p-value <0.001. The spatial component, Wy has values of 0.01, except the 90% which is <0.01, with a p-value <0.005, for both pollutants. Standard errors (provided in parenthesis).

(a)

	OLS	10%	20%	30%	40%	50%	60%	70%	80%	90%
Intercept	41.86 (0.38)	34.58 (0.36)	36.00 (0.4)	38.01 (0.55)	39.14 (0.5)	40.06 (0.56)	41.02 (0.58)	42.22 (0.6)	44.00 (0.78)	49.63 (1.37)
Children	-37.00 (2.33)	-27.28 (2.39)	-33.97 (2.45)	-40.75 (3)	-40.22 (3.32)	-40.49 (3.26)	-42.35 (3.25)	-44.32 (2.67)	-45.40 (3)	-28.37 (6.07)
Elderly	40.20 (2.25)	25.83 (3.06)	31.85 (3.01)	36.81 (3.43)	37.33 (3.28)	38.47 (3.36)	40.99 (3.08)	43.16 (2.67)	44.68 (3.85)	30.08 (3.97)
Economic deprivation Index	2.70	1.47	2.01	2.79	3.17	3.30	3.34	3.17	3.08	3.27

(0.14) (0.19) (0.17) (0.2) (0.18) (0.19) (0.19) (0.22) (0.32) (0.38)

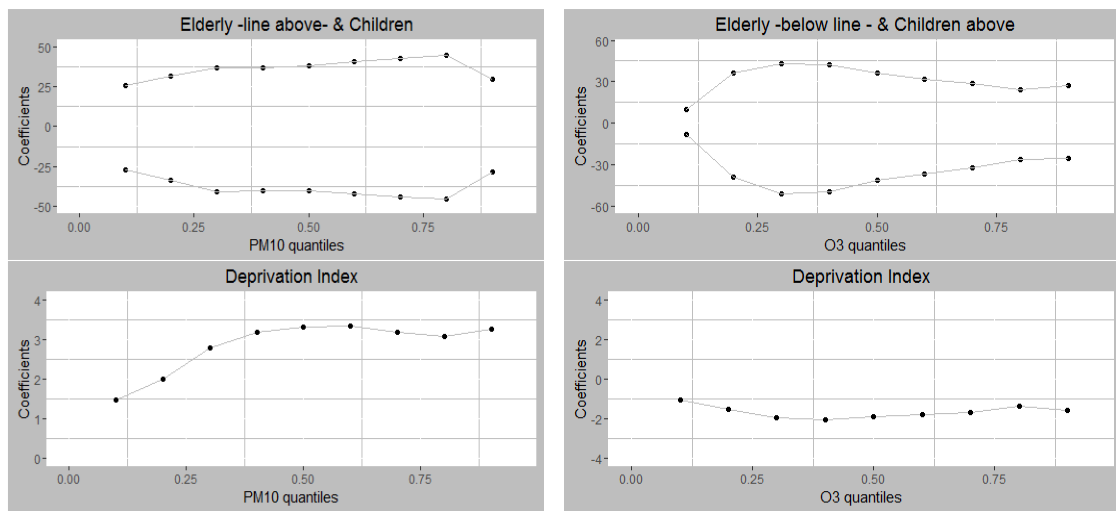
(b)

	OLS	10%	20%	30%	40%	50%	60%	70%	80%	90%
Intercept	57.50 (0.33)	49.74 (0.68)	53.53 (0.9)	56.70 (0.73)	57.94 (0.58)	58.76 (0.48)	59.72 (0.38)	60.46 (0.34)	60.99 (0.33)	61.47 (0.38)
Children	32.30 (1.99)	9.98 (3.79)	36.20 (4.16)	42.97 (2.66)	42.09 (2.57)	36.04 (2.53)	32.00 (2.55)	28.59 (2.62)	24.45 (2.76)	27.55 (2.49)
Elderly	-35.40 (1.92)	-8.04 (3.59)	-38.88 (3.11)	-51.02 (2.24)	-49.97 (2.62)	-41.62 (2.69)	-36.90 (2.49)	-32.67 (2.63)	-26.06 (2.99)	-25.75 (2.66)
Economic deprivation Index	-1.7 (0.12)	-1.05 (0.2)	-1.51 (0.27)	-1.92 (0.2)	-2.02 (0.16)	-1.87 (0.16)	-1.79 (0.17)	-1.66 (0.17)	-1.39 (0.17)	-1.59 (0.17)

I found similar results between the mean of the OLS and the 50% quantile (of the spatial quantile regression) for each explanatory variable (except for elderly people where the difference was around 6 units for the case of ozone). However, the spatial quantile regression outcomes showed a clear variation in the relationship of PM<sub>10</sub> with the economic deprivation index and elderly people, except the 90% for elderly (see table 2.4a and figure 2.2). Regarding the economic deprivation, the quantile estimators showed that within the 80% and 90% quantiles, PM<sub>10</sub> levels of pollution were more strongly positively associated with the economic deprivation index than the lower quantiles (the 10% and 20% quantiles). The variation was almost two times larger in the right tail (3.2) than the left one (around 1.7). Figure 2.2, left side, also shows a general increasing trend of estimators across the lower and upper levels of PM<sub>10</sub>. With respect to elderly people, higher levels of PM<sub>10</sub> were more strongly positively associated with higher percentage of elderly people within the higher quantiles of the distribution with  $\beta=43.9$ , (averaged for the 70% and 80% quantiles) than within the lower quantiles with  $\beta=28.8$  (averaged for the 10% and 20% quantiles). Therefore, these results showed that the average estimates,  $\beta=40.2$  and  $\beta=38.4$ , provided by the OLS and the 50% of the spatial quantile regression respectively, were lower with respect to the values of the higher quantile estimates but

above the values of the lower quantile estimates of PM<sub>10</sub>. Figure 2.2, left side, also illustrates a raised pattern from the 10% to 80% quantiles for elderly people and PM<sub>10</sub>. Note that these results do not report an interesting heterogeneity for the different levels of PM<sub>10</sub> and its association with the percentage of children in each AGEB.

The variation between ozone higher and lower levels and deprived economic conditions and vulnerable age groups was not clear (see table 2.4b and figure 2.2, right side). For example, there was no significant variation in the negative association of ozone with the deprivation index or the percentage of elderly people, at higher and lower levels of concentration. Nevertheless, I can identify some patterns. At lower levels of ozone,  $\beta=-38.8$  and  $\beta=-51$ , (20% and 30% quantiles) the elderly people had a stronger negative association with this pollutant than when ozone was at its upper levels,  $\beta=-26$  and  $\beta=-25.7$ , (80% and 90%). Likewise, within the upper quantiles, of ozone pollution, the level of pollution,  $\beta=26$  (averaged at the 80% and the 90% quantiles), was more strongly positively associated with the percentage of children in the AGEB than in the lowest quantile,  $\beta=9.9$  (10% quantile).



**Figure 2.2:** Spatial quantile regressions with different quantiles of PM<sub>10</sub> (left) and ozone (right) as response variables. These figures show the coefficients of elderly, children and deprivation index with the different quantiles of PM<sub>10</sub> and ozone (each dot represent from the 10% to the 90% quantiles).

The values of the spatial lag variable,  $W_y$ , were consistently small (all 0.01, except for the 90% quantile which was  $<0.01$ ) and significant,  $p$ -value  $<0.005$  across all quantiles,

suggesting that spatial autocorrelation is minimal for both pollutants over the full range of quantiles.

Importantly, the results of the spatial quantile model highlight the non-linearity of some associations across the all pollution levels, especially for PM<sub>10</sub> in relation to deprivation and percentage of elderly people; and for ozone in relation to the percentage of children. One-way ANOVA, which measures the precision of the different estimators across the quantiles of each pollutant, confirmed a high significant difference between such estimators ( $p$ -value < 0.005).

## 2.5. Discussion

The analysis investigated spatial heterogeneity, comparing exposure to higher and lower levels of each pollutant, PM<sub>10</sub> and ozone, across vulnerable groups in Mexico City. Overall, my results show a positive association between deprived economic conditions and PM<sub>10</sub> and a negative association between lower socioeconomic conditions and ozone. Even though the analyses focused on different levels of air pollution, which have been rarely studied, my findings are consistent with previous studies that focused on the mean of air pollution. The positive association of PM<sub>10</sub> with the deprivation index is congruent with previous literature (Briggs et al., 2008; Fecht et al., 2015). Moreover, other studies analysing PM<sub>2.5</sub> (Gray et al., 2013; Hajat et al., 2013) found a positive association between better socio-economic conditions and lower exposure of this pollutant. With respect to ozone and its negative association with deprivation index, my findings are also similar to previous research (Briggs et al., 2008; Gray et al., 2013). Conversely, Grineski et al. (2007) found a positive relation of ozone with more deprived economic status. With respect to vulnerable age groups, the findings show mixed evidence as previous studies: higher concentrations of PM<sub>10</sub> were significantly associated with higher proportions of elderly people but with lower proportions of children. With respect to children my results are similar to Fecht et al. (2015) and Carrier et al. (2014), with the latter study using PM<sub>2.5</sub>. Likewise, elderly people were to be found disproportionately exposed to other pollutants, SO<sub>2</sub> and NO<sub>2</sub>, (Clark et al., 2014; Zou et al., 2014) which is consistent with my outcomes. When considering ozone, the outcomes illustrate that elderly people are not

disproportionally exposed to this pollutant. Instead children were found to face disproportional exposure to ozone. Calderón-Garcidueñas and Torres-Jardón (2012) showed that children, living in the South of Mexico City, were highly exposed to ozone, which is congruent with my results.

The results highlight that the higher the PM<sub>10</sub> level is, the greater the level of disproportionate exposure of this pollutant to people in deprived economic conditions and with elderly people. Thus, the findings show that the association of the AGEBs with economic deprivation conditions was significantly heterogeneous on the different levels-quantiles of PM<sub>10</sub>, especially for the lower and upper concentration levels. In general, my results verify the hypothesis of an increasing pattern of this association from the lower to the higher quantiles of PM<sub>10</sub>. This is, higher levels of PM<sub>10</sub> were more strongly and positively associated with those AGEBs with deprived conditions than those with lower levels of this pollutant. This result is consistent with the findings of Rissman et al. (2013), who found a slightly decreased association between median income and concentrations of PM<sub>2.5</sub> pollution due to aircraft, from the 50 to 90% quantiles.. In the case of elderly group, I also identified an increasing trend of PM<sub>10</sub> exposure, from lower to higher quantiles (excepting the 90% quantile). This would imply that the health of these groups (those with deprived economic conditions and elderly people) is at risk due to high levels of PM<sub>10</sub> concentration. In Mexico City, elevated levels of this pollutant are more than double WHO's threshold levels, which were established to avoid health risks. Therefore, these specific groups should be targeted in pollution reduction policies at those locations.

The spatial distribution analyses partially explains the higher exposure of PM<sub>10</sub>, where traffic and industry processes are their principal sources (Querol et al., 2008), on deprived conditions and elderly people. Clusters of elderly people were found in the municipalities of Cuauhtémoc, Miguel Hidalgo and Venustiano Carranza, where the high proportion of this age group is due to lower fecundity rates and better medical services (Negrete 2003) than in other areas of the city. These areas are also (particularly Cuauhtémoc and Miguel Hidalgo), where most of the public services and jobs in Mexico City are located (Instituto de Políticas para el Transporte y el Desarrollo ITDP México 2015), attracting much commuter traffic. From 2008 to 2012 the vehicular fleet increased by close to 11%, this figure was elaborated based on the information of 'report of the quality of the air' (Instituto Nacional de Ecología y de Cambio Climático (INECC), 2013). Moreover,

Cuauhtémoc has two of the main and busiest avenues: 'Paseo de la Reforma' and 'Insurgentes'. Therefore, policies, such a congestion tax, in these two municipalities, that incentivize the use of low-emission public transport and less frequent vehicle usage would benefit the health of people living there by lowering the level of PM<sub>10</sub> emitted by vehicles. Such spatially-targeted policy has been applied in cities like Stockholm, Gothenburg and London (Leape, 2006; Börjesson & Kristoffersson, 2018). Central London, after the introduction of congestion charge in February 2003, experienced a reduction of about 20 percent on automobile traffic (Litman, 2005). This allowed to lower the pollution emitted by vehicles (Leape, 2006). Note that these policies may need an improvement of public transportation in advance; as it was the case in London, where there was an expanded bus lane system and major renovations to the subway system (Litman, 2005).

The association of deprived conditions and PM<sub>10</sub> can be explained using the arguments of Calderón-Garcidueñas and Torres-Jardón (2012) that less economically-privileged people spend considerable time in the traffic or close to it, walk long distances to take the crowded transport or work on the streets. In that sense an improvement in low-emission public transport, as mentioned above, would benefit the poorer communities as well. Moreover, note that the spatial analysis identified clusters of AGEBS with lower SES particularly in the north area, which includes the municipality of Gustavo A. Madero, which is recognised as one of the areas with the greatest concentration of people in poverty (CONEVAL, n.d.). This northern area (mainly the municipality of Azcapotzalco, Gustavo A. Madero) is also characterised by having many industries and main roads (Air Quality in Mexico City, 2014). This industrial character in the north is related to the availability of nearby facilities, new housing construction, and better quality infrastructure (Cruz & Garza, 2014). Therefore, spatially targeted policies could be implemented, in this northern area, to reduce PM<sub>10</sub> pollution from the industries there. This could be done by either obligating and/or incentivising better housekeeping, material substitution, recycling or process innovations (Cairncross, 1992; Willig, 1994).

My findings should be interpreted with some caution due to some methodological and data limitations. First, data on air pollution could be improved by using different modelling methods such as Atmospheric Dispersion Modelling System (Havard et al., 2009), Land-use Regression Models (Ryan & LeMasters, 2007) or other models such as Integrated Meteorological-Emission Models or Hybrid Models. This is because these

models use more variables and information such as traffic volumes, land-use, meteorology, topography to accurately model air pollution. However it is because of this extra information and special equipment and software (Jerrett et al., 2005a) that I could not use them in the study. I applied the universal kriging interpolation, which is based not only on the distance between the measured points but also on the overall spatial arrangement of the measured points to overcome this issue. One advantage of applying the kriging approach is the production of standard errors which quantify the degree of uncertainty of the spatial prediction, allowed me to identify the places with less reliable interpolation values (Mulholland et al., 1998). In that sense, I expect PM<sub>10</sub> pollution estimates in the south, where there are sparser data due to fewer monitoring stations, to have larger standard errors; meaning, that these errors may influence the results. As monitoring stations are not equally distributed across space, this problem is often acknowledged in the literature. For example, Künzli et al. (2005) obtained larger standard errors, as the result of universal kriging, on the periphery of Los Angeles metropolitan area with 23 monitoring stations. I followed Künzli et al. (2005) study by carrying out a sensitivity analysis to check the robustness of my regression outcomes, coming from the interpolated pollution values, especially for PM<sub>10</sub>. This involves down-weighting estimates with larger errors, in weighted least-square models (the weights specified as the inverse of the standard errors) and comparing the results with the main models with the universal kriging estimates. Thus, I accounted for the standard errors, obtained from the kriging interpolation, in the regressions. The outcomes were robust and similar to what I found in the original regression model, especially for ozone (results available in figure 2.A2 in Appendix). There was a variation of 6 units for elderly people after controlling for the standard errors for PM<sub>10</sub>, but the results for the other variables were quite similar to the original regressions. A second limitation of the approach is that I did not consider the mobility of people. It is difficult to measure the activity patterns of people, which is often ignored in the literature (Havard et al., 2009; Fecht et al., 2015); for example, where they spend more time, at home or in their jobs, and how far away they live from their jobs. This would require extensive data on behavioural patterns that were not available for my study site. Finally, while I recognised that alternative theories and approaches address the relationship between income and pollution (Martinez-Alier, 1995; List & Gallet, 1999; Yaduma et al., 2015; Stern, 2017), I followed existing literature on environmental justice (Rissman et al., 2013; Carrier et al., 2014; Fecht et al., 2015) by not making a specific attempt to explain the co-location of vulnerable groups and pollution.

This would have required me to control for the problem of reverse-causality (i.e., income may affect pollution through greater production levels, or the amount of pollution may affect income as people of low SES live in cheaper, but often also more polluted, areas), and for important omitting variables such as political or regulatory efforts, strong enforcement institutions, research and development activities or infrastructure (on this point see (Lin & Liscow, 2012; Germani et al., 2014). An alternative, longitudinal approach may have allowed us to gain additional insights into the chronological causal relationships that contribute to environmental inequalities (Briggs et al., 2008; Havard et al., 2011; Rissman et al., 2013), but such an approach is dependent on a suitable time series of data. Here, I used a cross-sectional approach to analyse the evidence for environmental injustice across all AGEBs in Mexico City, more than two thousand, facing heterogeneous levels of air pollution (particularly for those at the edge of the distribution, lowest and highest values).

Aside from these caveats, this study provides some distinct advantages over much previous work. I used spatial quantile regression, which shows the heterogeneous spatial distribution of the link between air pollution and vulnerable social conditions, with stronger unequal exposures for SES and elderly people in locations with upper levels of concentrations of PM<sub>10</sub>. Moreover, I used AGEBs, the smallest geographical units in Mexico City, and accounted for the spatial effect of clustering of the data set, and hence avoided producing biased estimators. These methodological aspects all contributed to enhancing the robustness of the results.



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## Chapter 3: Modelling local dynamic of term low birth weight in greater Mexico City: a Bayesian spatial-temporal approach.

### 3.1 Abstract

There is strong evidence that low birth weight (LBW) has a negative impact on infants' health. Children with LBW are more vulnerable to having disabilities due to metabolic disorders and are at higher risk of premature death. There has been a considerable amount of research on LBW risk, but only a small proportion of this research has examined local geographical patterns in LBW and the risk factors associated with these patterns. LBW is a particular health concern in Mexico, which has the highest rate of LBW in North America. The aims of this study are to: (i) model the change of LBW risk at the municipality level for the Greater Mexico City area, identifying municipalities with highest and lowest LBW risk; and (ii) explore the role of some socioeconomic and demographic factors in explaining variations in LBW risk. The study uses Bayesian spatio-temporal analysis to control for space-time patterning of the data. The analysis shows that most of the high-risk municipalities are in the west and most of the medium and low-risk municipalities are in the east and north respectively. Many municipalities show an increasing LBW risk over time, and the analysis highlights some municipalities which are currently medium risk but are likely to become high risk over time. Identification of high-risk municipalities may provide a useful input to policy-makers seeking to reduce the incidence of LBW, since it would provide evidence to support geographical targeting of policy interventions. The identification of education as an important determinant of LBW further suggests that a focus on wider social determinants, such as improving education and encouraging access to higher education levels, may help to reduce LBW in the Greater Mexico City area.

**Keywords:** Child health; term low birth weight; Bayesian spatio-temporal modelling; space-time variation; spatial random effects.

### 3.2 Introduction

There is an increasing policy interest in improving children's health, reflecting the United Nations' third Sustainable Development Goal (SDG 3) on good health and wellbeing, and particularly the SDG 3 target to end preventable deaths of new-borns and children under

five by 2030 (UN, n.d.). There are also two World Health Organization (WHO) programmes, 'Maternal, new-born, child and adolescent health (WHO, n.d. a)' and 'Global Strategy for Women's, Children's and Adolescent's Health 2016-2030' (WHO, n.d. b), which are focused specifically on improving the health of mothers and new-born children. Low Birth weight (LBW) is one of the risk factors associated with early childhood deaths and is linked with various metabolic disorders (Barker et al., 1993; Valsamakis et al., 2006; McGovern, 2018). Children with LBW are more likely to suffer from hypertension, coronary heart disease, type II diabetes and blood coagulation when they become adults (Osmond & Barker, 2000; Morley, 2006). These health impacts effects can have adverse impacts on lifespan and quality of life for individuals, as well as having economic implications for society. Given this policy interest and the SDG targets, there is a need to understand the factors behind LBW, so that policies can be developed to reduce the problem and its implications. LBW, when new-born infants weigh less than 2500g at birth (Abrevaya & Dahl, 2008) is one of the principal causes of neonatal mortality in many low and middle income countries. LBW is a major public concern in Mexico (Ministry of Health in Mexico, 2002). Here, 9.15% of children are born with LBW, which is the highest rate in North America, and one of the highest throughout the Americas. This paper focuses on understanding the spatial distribution and temporal evolution of LBW in the largest urban area in Mexico, Greater Mexico City, from 2008 to 2015.

The neonatal mortality rate (number of infant deaths in the first 28 days of life per 1,000 live births) has been decreasing in Mexico from 11.52% in 1990 to 8% in 2012, but these values are still considered high (Ministry of Health in Mexico, 2002; Ministry of Health in Mexico, 2014). In 2001, there were 110 daily deaths of infants under 1 year old (Ministry of Health in Mexico, 2002). According to the Ministry of Health in Mexico (2008), 60% of infant deaths (44,000) occur in the neonatal period, and around 45% of these neonatal deaths could be avoided with proper medical interventions. The Ministry of Health in Mexico has therefore created a number of public programmes to decrease the neonatal mortality risk. These include 'Programa de Accion: Arranque Parejo en la Vida, 2002', 'Programa de Accion Especifico 2007-2012, 2008' and Programa de Accion Especifico Salud Maternal y Perinatal, 2013-2018' (Ministry of Health in Mexico, 2002). In addition to individual-based maternal risk factors, other factors associated with high neonatal mortality and, by inference, LBW include neighbourhood-level factors such as



marginal and deprived economic conditions (Ministry of Health in Mexico, 2002). Understanding these neighbourhood-level factors can therefore make a significant contribution to reducing LBW risk and can serve as important evidence for policy makers. Specifically, understanding the geographical variation in LBW risk, and the factors underlying this, could provide information for the development of geographically targeted programmes that mitigate such risk in the most efficient way.

Previous studies on the spatial pattern of LBW have used spatial heterogeneity measures such as the Moran Index and local indicators of spatial association (LISA) to identify areas with high or low LBW risk (Francis et al., 2012; Tu et al., 2012; Tian et al., 2013). Studies such as Tu et al. (2012) and Tian et al. (2013), which analysed patterns of LBW in the state of Georgia, USA, focus on spatial analysis in a given year or within a specific period of time. Analyses that combine space and time can provide greater insights into public health issues because of the combined spatial and temporal structure of much disease data (Shin et al., 2012; Blangiardo et al., 2013; Lawson, 2013; Papoila et al., 2014), and the ability to link these patterns to underlying spatio-temporal variation in socio-economic conditions and other risk factors. Examples of research which has taken this type of approach include studies using conditional autoregressive spatio-temporal Bayesian models for the mapping and analysis of mortality risk from brain cancer (Ugarte et al., 2015) and gastric cancer (Aragonés et al., 2013).

There are several studies (Pearl et al., 2001; Baker & Hellerstedt, 2006; Young et al., 2010) that have explored the relation between LBW and demographic or socioeconomic determinants. For example, having prenatal care and being a young mother have a significant effect in reducing the probability of having a child with low birth weight (Torres-Arreola et al., 2005; Insaf & Talbot, 2016). Married mothers and mothers who have no more than two children also have a lower risk of LBW (Pearl et al., 2001; Frank et al., 2004). However, few studies have accounted for the spatial (Insaf & Talbot, 2016) or spatial-temporal structure (Kirby et al., 2011) of the data, either in relation to health outcomes or their determinants. Knorr-Held and Besag (1998) acknowledge that communities are often clustered with respect to their socioeconomic background. Hence, it is likely that people with higher socioeconomic status live close to each other, supported by good services in terms of schools and housing, whereas people with lower socioeconomic status are clustered in other places with poorer services. Socioeconomic

status may also vary across time for both individuals and neighbourhoods, with important influences on health risk (Knorr-Held & Besag, 1998). Therefore, the association between LBW risk and socioeconomic factors may vary over space and time, and these types of spatio-temporal variation in risk have been observed for stomach cancers (Papoila et al. (2014) as well as air pollution (PM2.5) and asthma (Lawson et al., 2012). Moreover, the health risk of certain portions of the population may vary over space and time due to changes in health-related behaviours such as physical activity, smoking and diet (Shin et al., 2012).

There are also statistical and policy-related reasons for accounting for the spatio-temporal structure of health problems. Not accounting properly for space and time structure in the data can lead to errors with spatial autocorrelation and serial correlation respectively. In these cases, assumptions regarding the independence and identical distribution of the residuals would not be met, with a consequence that estimators of effect size may be biased or incorrect (Anselin, 2002; Dormann et al., 2007) (Harvey, 1990). Even when these components are taken into account, endogeneity may still exist due to omitted factors that may have an impact on LBW risk when space and time are considered simultaneously. An example of one such spatio-temporally related factor that affects LBW is smoking during pregnancy (Baker & Hellerstedt, 2006). Most previous studies in the area of LBW have not controlled for this spatial-time effect which may bias estimators upwards, although Kirby et al. (2011) is one exception, which accounts for this spatial-temporal variation with Bayesian latent structures models.

The aim of the study was therefore twofold. Firstly, I aimed to model the change in LBW risk across time for each municipality in Greater Mexico City. I did so by characterising the evolution of high, medium and low risk municipalities (model 1). High risk locations should be a priority for policy attention, so this analysis provide important baseline information for decision-makers. Secondly, I considered the extent to which these overall levels of risk could be explained by various socioeconomic factors at municipality level, controlling for spatio-temporal variability in these factors (model 2). Where known socioeconomic risk factors contribute significantly to risk, the level of residual risk is lowered, reducing uncertainty around potential policy interventions. However, where known socioeconomic risk factors do not contribute to the level of risk, a high level of residual risk remains unaccounted for, and more investigation would be needed to obtain

evidence to support specific policy interventions. I applied a Bayesian modelling approach (Bernardinelli et al., 1995), since this provides a flexible framework to model space, time and space-time structure of the LBW data through random effects which can capture the unobserved heterogeneity. While the Bayesian analysis of space-time variability, using a two-stage classification method, has been applied in the area of criminology (Li et al., 2014), to my knowledge, this is the first time that this methodology has been used to account for the space-time structure of LBW risk.

### 3.3 Data and Methods

#### 3.3.1 Area of study

Greater Mexico City, one of the most populated urban areas in the world, is the third largest metropolis in OECD countries, and the largest in the world outside Asia (OECD, 2015). It consists of 16 municipalities within Mexico City and 59 municipalities of the State of Mexico. It had 20,892,724 inhabitants in 2015, according to the Mexican National Institute of Statistics and Geography (INEGI), with a land area of 7,866 square kilometres. It is considered the most important metropolitan area in Mexico in terms of the economy, producing 23% of the country's gross domestic product in 2010 (OECD, 2015).

#### 3.3.2 Low birth weight, economic, social and education data

The analysis explored low birth weight records in a total of 75 municipalities. The birth weight records data were obtained from the Ministry of Health for all registered births in the municipalities of Greater Mexico City from January 2008 to December 2015 (n=2,538,293). The analysis was restricted to those babies with a birth weight of <2500g during the normal period of gestation from 37 to 42 weeks, known as term low birth weight (TLBW). This resulted in a final dataset of 2,334,398 birth records. This information was aggregated at the municipality level, since this represented an appropriate balance between computational demands and model complexity.

According to the literature, having prenatal care and being a young mother are significant factors associated with a higher LBW risk (Torres-Arreola et al., 2005; Insaf & Talbot, 2016). The marital status of the mothers and their parity have also been identified as risk factors associated with LBW (Pearl et al., 2001; Frank et al., 2004). Therefore, following

previous studies and according to the availability of data, the following variables were included in models at the municipality level: marital status (mothers who are married or in a free union), low education level (those without education or who did not finish primary school), those with a high education (Bachelor's degree level), mothers aged over 35 years old, parity (mothers who have no more than 2 children) and prenatal care (those that received prenatal attention). All these explanatory variables were expressed as a percentage. The response variable was the number of TLBW records for each of the 75 municipalities.

As an initial explanatory analysis, I plotted the temporal trend of TLBW of Greater Mexico City over the 8 years. To illustrate the potential spatial and temporal correlation of the TLBW data, the Global Moran Index (Anselin et al., 1996) and Auto Correlation Function (ACF) statistical tests were executed respectively. Figure 3.1 shows the observed TLBW risk for Greater Mexico City over the 8 years period of study. There is a significant decrease in TLBW risk from 2010 to 2011 (see the Discussion section for more details). The Global Moran Index of TLBW for each year was positive and significant with a mean value of 0.35 and a p value < 0.0001, showing positive spatial autocorrelation in the TLBW data. This implies that there is some clustering of TLBW risk in Greater Mexico City. The ACF (serial correlation) mean, across all the municipalities, was 0.42, which was lagged 1 year for each municipality; only two municipalities had negative values. This illustrates evidence of temporal autocorrelation, and hence, the association on a certain level of the observed TLBW data over time.

**Figure 3.1. Observed TLBW risk in Greater Mexico City, 2008-2015**

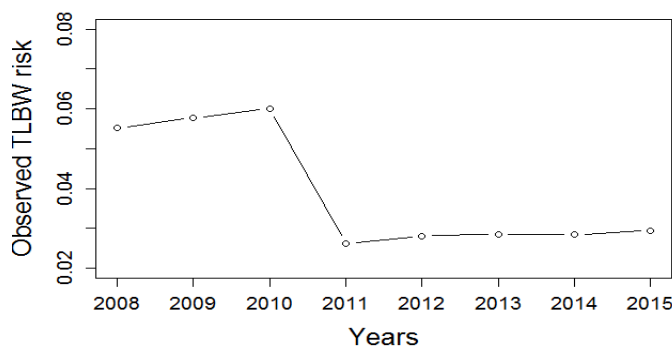


Figure 3.1 shows the observed TLBW over the study period (2008-2015).

The residential addresses of the mothers were linked to the INEGI intercensus data in 2015 to complement the social factors and derive the economic factors. These variables, all expressed as percentages, were: households with a medical service, either public or private (social variables), households with a TV, households with a car, households with a computer, households with a land line, households with a mobile phone and households with internet. These economic variables were combined, using a principal component analysis, to derive an economic index which represents purchasing power at the municipality level. This economic index was transformed into a categorical variable with three categories: poor, middle and rich. The same socioeconomic variables, at the municipality level, have been used in previous studies as covariates of LBW risk (Kirby et al., 2011; Insaf & Talbot, 2016).

### 3.3.3 Patterns of TLBW risk (model 1)

The analysis uses a Bayesian approach with a hierarchical structure to capture the potential spatial, temporal and spatio-temporal structure of the data. Given the form of the outcome variable, the probability of having a child with TLBW or not, I assume a binomial likelihood (McCullagh & Nelder, 1989),  $y_{it} \sim \text{Binomial}(n_{it}, \mu_{it})$ . In the model:  $y_{it}$  are the number of cases of TLBW in each municipality  $i$  over year  $t$  within the studied period;  $n_{it}$  represents the number of birth records in the municipality  $i$ ; and  $\mu_{it}$  represents the TLBW risk. Following Law et al. (2014) and Li et al. (2014), the underlying risk of TLBW is modelled as:

$$\text{logit}(\mu_{it}) = \alpha + (s_i + u_i) + \gamma_0 t^* + v_t + \gamma_1 i t^* + m * g_t + \varepsilon_{it} \quad (1)$$

where  $\alpha$  is the overall logit TLBW risk across the 8-year period; the terms  $s_i$  and  $u_i$  account for the spatial dependence, and  $\gamma_0 t^*$  is the overall linear time trend which accounts for temporal dependence alongside  $v_t$ , a Gaussian noise, to account for nonlinearity in the temporal trend, where  $v_t \sim N(0, \sigma_v^2)$ . The spatial component  $(s_i + u_i)$  uses the BYM (Besag, York and Mollié) model (Besag et al., 1991). Within this model,  $s_i$  represents the spatially structured and  $u_i$  the spatially unstructured random effects, where  $u_i$  follows a Gaussian distribution and  $s_i$  follows an intrinsic conditional autoregressive (ICAR) prior model. This term takes into account the potential spatial autocorrelation which means that neighbouring areas are more likely to have similar

values. In other words, nearby municipalities are assumed to have similar TLBW risk. Thus,  $s_i$  includes a spatial adjacency matrix  $W$  of size  $N \times N$ , where the diagonal values are  $w_{ij} = 1$  if municipalities  $i$  and  $j$  share a common boundary, otherwise  $w_{ij} = 0$ .

After accounting for spatial and serial correlation, it is likely that there would be some potential variation in the residuals, illustrating some remaining endogeneity, due to the interaction between space and time. Model [1] captures this effect with  $\gamma_{1i}t^*$  and with  $\varepsilon_{it}$ , where the spatial-temporal component ( $\gamma_{1i}t^*$ ) represents and assumes a linear departure of the local temporal trend of each municipality from the common trend; this can be increasing, decreasing or have a stable tendency from the overall linear pattern. Each municipality would have different trends, but their values would be expected to be similar to the nearby ones.  $\gamma_{1i}t^*$  follows the same BYM prior as the spatial component.  $\varepsilon_{it} \sim N(\sigma_\varepsilon^2)$  is the component for the variability that is not explained by the other terms. This may include overdispersion which indicates a higher variation of the observed TLBW data compared with its mean, due to the nature of the binomial distribution. All random effect standard deviations such as  $\sigma_v^2$  and  $\sigma_\varepsilon$  have a positive half Gaussian prior  $N_{+\infty}(0,10)$  following the Gelman (2006) criterion. Finally, I control for the sharp drop of the observed TLBW in Greater Mexico City from 2010 to 2011 with  $m * g_t$  to simplify the interpretation of the overall trend. The  $g_t$  dummy vector has 0 (before the drop) and 1 (after the drop) values, and  $m$  assumes a normal distribution. Possible factors contributing to the observed drop in TLBW between 2010 and 2011 are outlined in the Discussion.

To identify municipalities of high, medium and low LBW risk, I obtained the posterior probability of the spatial component  $p(\exp(u_i + s_i) > 1 | data)$ . The expression  $\exp(u_i + s_i)$  indicates the average TLBW risk (over the eight years) for each municipality with respect to  $\alpha$ , the Greater Mexico City average. Following the criterion used in previous studies (Richardson et al., 2004; Li et al., 2014) to classify the different categories of each municipality, I classified those municipalities with values greater than 0.8 as high risk, and those with values less than 0.2 as low risk. Therefore, those municipalities with values in the middle, between 0.2 and 0.8, were classified as medium risk. Following Li et al. (2014), I classified each municipality as  $hi = 1, 2$  or  $3$  if they were high, low, or medium risk, respectively. Once these categories have been

established, in order to explore how each municipality changed across time, I measured its local dynamic over the study period as increasing, decreasing or stable. For this purpose, I applied the posterior probability to the local slopes  $p(\gamma_{1i} > 0 | h_i, data)$ . If the probability is higher than 0.8, then this particular municipality presents an increasing trend relative to the overall trend. If the probability is less than 0.2 then these municipalities have a decreasing trend in risk relative to the overall trend. Otherwise, if the probabilities values are between 0.2 and 0.8, then these municipalities have a time trend in risk that is similar to the overall trend.

### 3.3.4 Role of socioeconomic factors in contributing to TLBW risk (model 2)

To determine the extent to which the spatial-temporal variability of TLBW risk in Greater Mexico City could be explained by known socioeconomic risk factors, I added to the model [1] a set of covariates:

$$\log(\mu) = \alpha + \beta X + v_t + (u_i + s_i) + \gamma_0 t^* + \gamma_{1i} t^* + m * g_t + \varepsilon_{it} \quad (2)$$

Where  $X$  represents a vector of the 8 following socioeconomic and demographic covariates: marital status (mothers who are married or in a free union), low education level (those without education or who did not finish primary school), those with a high education (Bachelor's degree level), mothers aged over 35 years old, parity (those who have no more than 2 children), prenatal care (those that received prenatal attention), those having a public or private medical service, and the economic index. I assigned the following noninformative priors  $N(0, 1,000)$ , with normal distribution, a mean of zero and a large variance ( $=1,000$ ), to each of the regression coefficients,  $\beta$ , due to the absence of genuine prior expectations.

The models were implemented in R (statistical software) using the coda and R2WinBUGS packages to call the WinBUGS software. I ran two MCMC chains with different initial values for each model. I used 69,998 and 79,402 iterations for model 1 and 2 respectively for making inferences, after having burned in off the first 30,000 and 25,000 iterations for model 1 and 2 respectively. The convergence was examined by looking at the trace histories and the Gelman diagnostics; the values were below of 1.04 for each model parameter, showing that they had achieved convergence (Gelman & Rubin, 1992).

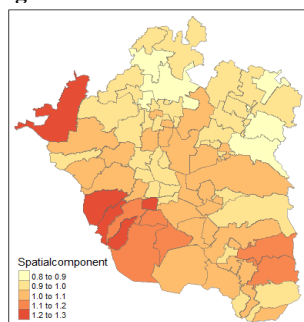
## 3.4 Results

### 3.4.1 Local geographical evolution of TLBW risk

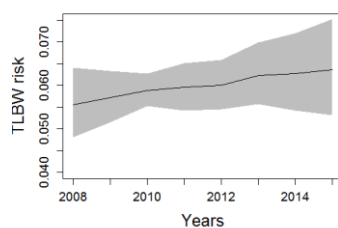
Figure 3.2a shows the relative risk of having a child with TLBW in each municipality compared to the average over the studied period (model 1). A relative risk value that is above (or below) 1 suggests a higher (or a lower) risk for this municipality compared to the Greater Mexico City average across the 8 years. Results illustrate that areas in the west are characterized by having higher risks of TLBW, whilst areas in the north and north east have lower risks of TLBW. Figure 3.2b illustrates the overall time trend of relative risk (controlling for the sharp reduction from 2010 to 2011), compared to the Greater Mexico City average from 2008 to 2015. Overall, there is a slight increasing tendency of TLBW risk.

**Figure 3.2a, 3.2b and 3.2c. Spatial risk, overall trend and local trends (including the overall trend) of each municipality in Greater Mexico City.**

**Figure 3.2a**



**Figure 3.2b**



**Figure 3.2c**

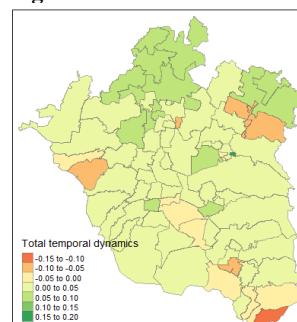


Figure 3.2a. shows the spatial component of TLBW risk during the studied period. Those areas with a relative risk value greater than (less than) 1 have a higher (lower) relative risk compared with the average. Figure 3.2b displays the overall time trend in relative risk with 95% CI, after accounting for the drop in 2010-11. Figure 3.2c shows the local trends of each municipality respect to the overall trend; positive (negative) values have higher (lower) increase in TLBW risk relative to the overall trend during the studied period.

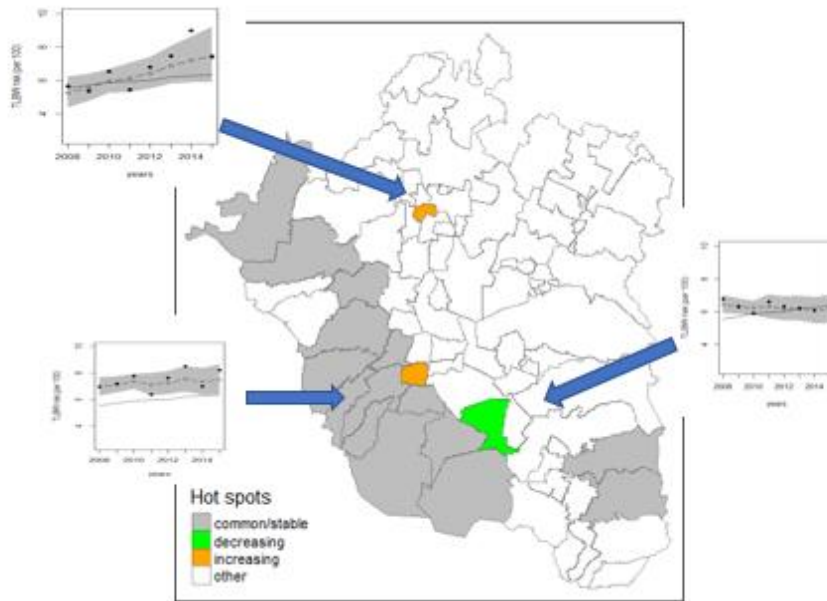
The posterior means of the local temporal trends, which include the overall linear trend, are displayed in figure 3.2c. Those municipalities with negative (positive) values present a slower (higher) increase in TLBW risk over the 8 years. Overall, there is a faster increase in TLBW risk in the northern area, although with a few exceptions.

After having identified the relative risk of TLBW risk across Greater Mexico City (figure 3.3a), these values were used (as described in the statistical analysis section) to classify the municipalities as high, medium or low risk overall; see figures 3.3a, 3.3b and 3.3c respectively. High risk municipalities are located in the west and southwest of the city



with a few high risk municipalities in the south. In contrast, most of the low risk municipalities are located in the north. Medium risk municipalities are mostly in the east and centre.

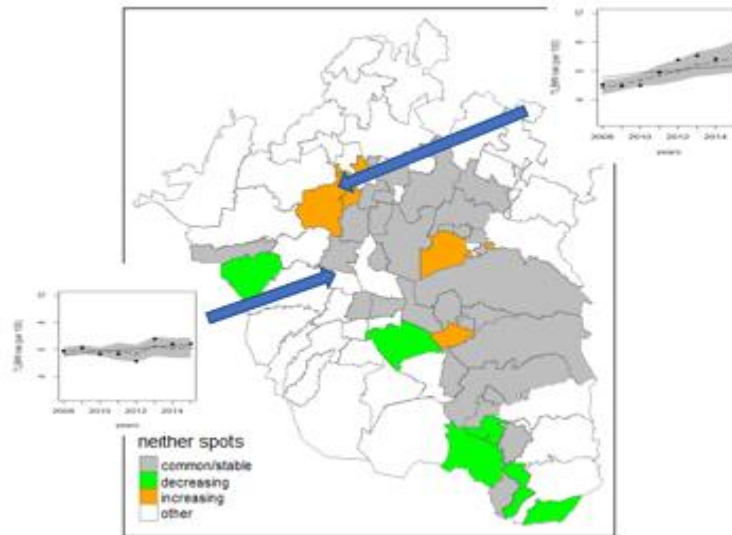
**Figure 3a. Temporal trends in TBLW risk for high-risk municipalities**



**Figure 3.3a** displays the temporal dynamics of TBLW risk for high-risk municipalities in greater Mexico City, which are classified into 3 categories: stable, decreasing and increasing risk. The inserted figures show the observed TLBW risks (per 100 inhabitants; the black solid dots), the estimated TLBW risks -posterior means of risks-(open circles and dashed line) with 95% CI (grey region) and the estimated common trend (black line) over time.

To illustrate the temporal dynamics of LBW risk in the municipalities, I classified the municipalities in three categories according to their LBW risk: stable, decreasing and increasing. The graphs in figures 3.3a, 3.3b and 3.3c show the different trends for the observed TLBW risk, the estimated TLBW risk and the estimated common trend. Figure 3.3a shows that most of the high risk municipalities (83%) had a stable dynamic, whereas just two of the high-risk municipalities (representing 11%) had an increasing trend in LBW risk. Figure 3.3b shows the medium risk municipalities, of which 13% showed an increasing trend in risk (13%).

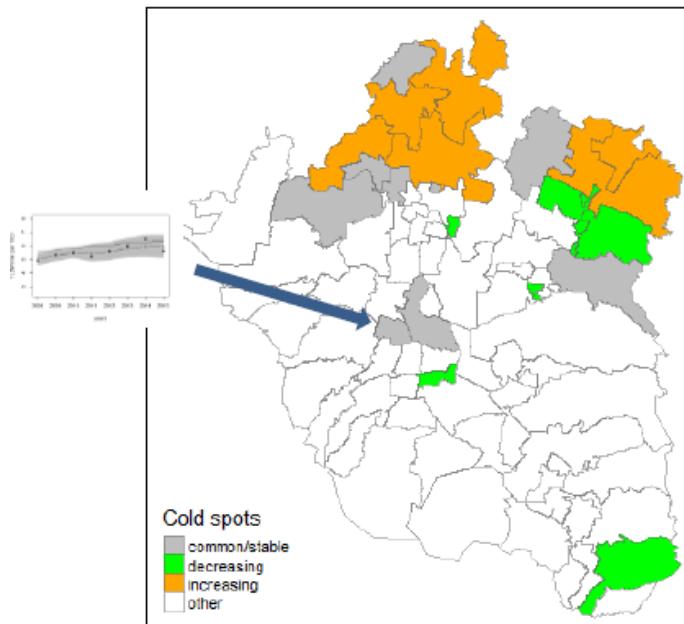
**Figure 3.3b. Temporal trends in TBLW risk for medium-risk municipalities**



**Figure 3.3b** displays the temporal dynamics of TLBW risk for medium-risk municipalities in greater Mexico City, which are classified into 3 categories: stable, decreasing or increasing risk. The inserted figures show the observed TLBW risks (per 100 inhabitants; the black solid dots), the estimated TLBW risks (open circles and dashed line) with 95% CI (grey region) and the estimated common trend (black line) over time.

Finally, Figure 3.3c illustrates that an important number of low risk municipalities (almost 30%), mainly located in the north and northeast, showed a relative increase in TLBW risk over time.

**Figure 3.3c. Temporal trends in TBLW risk for low-risk municipalities**



**Figure 3.3c** displays the temporal dynamics of TLBW risk for low-risk municipalities in Mexico City, which are classified into 3 categories: stable, decreasing or increasing risk. The inserted figures show the observed TLBW risks (per 100 inhabitants; the black solid dots), the estimated TLBW risks (open circles and dashed line) with 95% CI

(grey region) and the estimated common trend (black line) over time.

### 3.4.2 Role of socioeconomic factors in determining TLBW risk

The posterior means of the spatial-temporal model and the 95% credible intervals are presented in the Table 3.1 (model 2); women with bachelor's degrees were excluded due to the high correlation of this variable with the other covariates (Pearson correlation  $r > 0.55$  with a  $p$  value  $< 0.001$ ). Results in this table illustrate that mothers without education or who did not complete primary school (lower education) have a significantly higher risk of TLBW; a 1% increase in mothers with low education results in a 0.5% increase in TLBW risk (a factor of 1.005 with 95% CI 1.000-1.010). The rest of the predictors are not significant at the 95% CI. However, other factors such as marital status, mother over 35 years old, parity and medical service were significant at the 90% level. From this set of variables, the only one which had the expected directionality was that relating to mothers over 35 years old, who are more likely to have a child with low birth weight. The economic index was not significant and did not have any impact on TLBW risk.

**TABLE 3.1** Posterior means of relative risks, with 95% uncertainty displayed in the brackets.

Relative risk	Description	Posterior estimates
Marital Status	Mother who are married or in free union/individual*	1.009 (0.999, 1.018)
Not/low education	Not education or did not complete primary school/individual*	1.005 (1.000, 1.010)
Mother age over 35	Individual*	1.004 (0.994, 1.014)
Prenatal care	Individual*	0.993 (0.938, 1.005)
Parity	With not more than two children/individual*	1.003 (0.995, 1.010)
Medical service	With medical service/census variable	1.002 (0.997, 1.007)
Economic index <sup>1</sup> (middle)	Purchasing power/ census variable	0.965 (0.911, 1.023)
Economic index <sup>1</sup> (high)	Purchasing power/ census variable	1.009 (0.935, 1.023)

Note: <sup>1</sup>The economic index variable is categorical (poor, middle and high), the poor is the reference and equal to zero.

\* means that the data were aggregated from the individual level.

The figures between the brackets indicate the Credible Interval (those values covering 1 means that the factor-variable is not significant).

The addition of socioeconomic covariates explained a considerable amount of the risk for all 18 high risk municipalities, moving them into a low risk category in terms of residual risk. The low levels of residual risk for the 18 high risk municipalities suggest that for these municipalities, the socioeconomic covariates that were added to the model explain much of the risk. The addition of the socioeconomic covariates resulted in low residual risk for 11 of 22 low risk municipalities, suggesting that these covariates explain the risk levels in half of the low risk areas. Therefore, there are some other unobserved factors which must explain the overall risks in half of the low risk municipalities.

### 3.5. Discussion

This study has examined the temporal dynamics of TLBW risk across municipalities in Greater Mexico City Mexico City and investigated some socioeconomic and demographic factors to explain differences in risk. To the best of my knowledge this is the first work in this area which has accounted for space, time and space-time patterns by applying a two-stage classification method incorporating random effects using a Bayesian approach (Li et al., 2014).

More than half of the high-risk municipalities were in the south and west of Mexico City rather than the surrounding area. This result may appear unexpected, since Mexico City, as the capital, has better medical facilities, higher levels of income and education. However, a previous study based on a literature review of low birth weight in Mexico, found that Mexico City had a higher rate of LBW than any other State in Mexico (Buekens et al., 2013). Within the high-risk municipalities, Benito Juarez and Melchor Ocampo both showed an increasing risk over the period studied. These results may be explained by the fact that Benito Juarez is one of the municipalities in Mexico City with a higher population density of women. It also has a high number of jobs compared with other municipalities in Greater Mexico City, and is one of the most dynamic municipalities in terms of transport mobility (DENUE, 2009), which leads to a high level of exposure of its inhabitants to air pollution. Air pollution has previously been considered as increasing LBW risk (Coker et al., 2015). Meanwhile, Melchor Ocampo is

characterized by low levels of education and income (figure 3.B1, Appendix part), and low education was found to be associated with TLBW risk. Besides, Melchor Ocampo is located near to the northern industrial area which may also lead to higher exposure to air pollution (Air Quality in Mexico City, annual report 2014). Similarly, the medium-risk municipalities which showed a tendency for increasing risk over time are close to industrial areas. For instance, the municipalities of Cuatitlan and Cuatitlan Izcalli are in the industrial cluster in the north of Mexico City. Meanwhile, the municipalities of La Paz and Atenco are within and close to the industrial cluster of La Paz, in the eastern part of Mexico City. A significant number of the low-risk municipalities (almost 30%) in the north of the city also have an increasing tendency of TLBW risk over time. The northern areas in the study area, in the State of Mexico, are characterized by lower socioeconomic and education levels than Mexico City (see figure 3.B1 in the Appendix).

After controlling for the sharp reduction from 2010 to 2011, the relative TLBW risk shows an increasing trend over the 8-year period of study. The sharp decrease in the LBW risk in 2010-11 (a decrease of 55%) was not explained by a decrease in the number of births, since this varied by only around 3% over time. The decrease in the LBW risk may have been partly the result of different health programmes (see Introduction), but none of these programmes started in 2010). Alternatively, it could reflect a change in how data were collected. There are no detailed records of methodological changes in data collection, although Buekens et al. (2013) reported that the quality of birth weight reporting is difficult to evaluate. However, the reason behind the reduction of LBW from 2010 to 2011 remains unclear.

My analysis highlighted lower education as a factor that increases TLBW risk, which is similar to findings from previous studies (Luo et al., 2006; Young et al., 2010). For instance, Young et al. (2010) found a positive relation between infant birth weight and maternal higher education for mothers living on Cape Cod, Massachusetts. With respect to economic status, my income index (proxy variable of income) was not significantly associated with TLBW risk. This finding is similar to another study (Cubbin et al., 2008) where income was found not to be significant in Washington, USA. However, other studies (Masi et al., 2007; Kirby et al., 2011) have found income to be a significant, positive determinant of LBW. Kirby et al. (2011) concluded that household median income is negative associated with LBW risk, across the states of Georgia and South

Carolina. These results may differ because of differences in methodology, such as the use of different types of regression model, different geographical units of analysis and variations in local context.

These results should be interpreted with caution due to some methodological and data limitations. This is particularly true for analysis of covariates of TLBW. I used covariates at the municipality level, but this potentially masks important variations within municipalities, and to obtain more reliable results on the role of covariates in explaining TLBW risk, it would be better to analyse birth records at the individual level; this would be a priority for future work. However, key strengths of this study include the specific inclusions of time, space and space-time structures, which are important to take into account due to the nature of the data. Because the analysis controls for any unobserved heterogeneity, it is possible to derive more robust estimators.

McLaughlin et al. (2007) highlighted the importance of robust data analysis alongside the knowledge of the local context as inputs for policy decisions, and in enhancing the effectiveness of policy. In the area of health, Ugarte et al. (2015) illustrated that spatial and temporal trends provide useful information for policy makers in designing programmes to tackle health inequalities. The findings of this study, showing the spatial evolution of TLBW risk, may therefore provide an important input to decisions on policy to reduce TLBW risk. The identification of municipalities at highest risk of TLBW would permit the geographical targeting of policy efforts to reduce LBW risk, which could offer significant benefits in terms of developing cost-effective policy, given the overall scarcity of healthcare resources in Mexico. In particular, the identification of current medium-risk municipalities which show how an increasing risk over time could be important in developing more proactive geographically-targeted policy initiatives. Geographical targeting of policy may also bring benefits in enhancing the confidence and capacity of the local participation, which would in turn increase the impact of such policies (Smith, 1999; Tunstall & Lupton, 2003). The results of the analysis of contributing socioeconomic and demographic risk factors also provide some potential levers for policy-makers to address as a means of influencing LBW risk. Importantly, they suggest that a focus on reducing broader social determinants of LBW through social programmes, such as improving education and encouraging access to higher education levels, would be likely to bring benefits in reducing the incidence of LBW (Kirby et al., 2011).

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## Chapter 4: Health impact of natural disasters: evidence from Mexico

### 4.1 Abstract

In the last decades, there has been a significant increase in natural disasters that exceed local response capacity, negatively affecting people's health and causing large economic losses. Vulnerable groups in society experience the greatest health burden from such events. Building disaster resilience requires taking the necessary steps to improve the capacity of environmental, social and public health systems, to cope with the consequences of disasters, and improve preparedness. The aim of this study is to explore the association of morbidity and physical incapacity of vulnerable age groups (children and elderly) with exposure to natural disasters in Mexico. The focus is on the adverse effects that may extend well beyond the disaster itself and its immediate aftermath. Using household-level data from official Mexican Household Surveys on self-reported current health status following natural disasters over a five-year period, this paper develops a zero-inflated binomial model of health indicators as a function of experience of natural disasters, education, income, and other health determinants. The results provide evidence that children and the elderly are disproportionately affected by the morbidity and physical incapacity impacts of natural disasters, when compared with non-elderly adults in the population. The results also highlighted the role of education in reducing the impacts of natural disasters. Improved monitoring of health and targeted health and social programmes may help to mitigate the negative effect of these natural disasters. The effectiveness of these programmes is likely to be enhanced by targeting vulnerable groups in the population, such as children and the elderly, so that they can prepare more effectively for disasters and be better equipped to mitigate the adverse health effects when disasters occur (Baez & Santos, 2007). A broad base for these programmes, including educational initiatives, is likely to enhance their success in reducing the negative health impacts of natural disasters in the medium and long term.

**Keywords:** Natural disasters, health impact, vulnerable groups, morbidity, physical incapacity.

### 4.2. Introduction

There has been a significant increase of natural disasters in the last decades (Helmer &

Hilhorst, 2006; Van Aalst, 2006; Baez & Santos, 2007; Guha-Sapir et al., 2014), with severe impacts on human lives, people's health, the environment and the economy (Vos et al., 2010; Gaire et al., 2016); Field et al. (2012); World Bank, 2010). Thomas and López (2015) estimated that the frequency of natural disasters recorded in the Emergency Events Database (EM-DAT)<sup>4</sup> increased from over 1,300 events in 1975–1984 to over 3,900 in 2005–2014, and reported over 1 million deaths and a cost of damage estimated at over \$1.7 trillion since 2000. WHO (1992) and UNISDR (n.d.) define a disaster as “a serious disruption of the functioning of a community or a society causing widespread human, material, economic or environmental losses which exceed the ability of the affected community or society to cope using its own resources”. Natural disasters are linked to hydrometeorological, climatic, biological or geophysical hazards, that often occur suddenly and abruptly, and may be aggravated by human activities. Moreover, the likelihood of such hazards becoming disasters is related to the vulnerability and the social and financial coping capacity of the human communities or populations being exposed to them. Poorer countries, poorer communities, and vulnerable groups within these communities are therefore all at greater risk of experiencing disasters and being less resilient to them. Because of this, the economic impacts of disasters tend to be more severe for low- and middle-income countries than for high-income countries (Gaire et al., 2016). Mexico has the highest number of natural disasters of all the countries in Central and South America and the Caribbean, with the southern Mexican states being especially vulnerable to disasters (Maynard-Ford et al., 2008). Mexico is a middle-income country with high levels of poverty and inequality, and therefore one in which the social, health and economic impacts of natural disasters would be expected to be severe. Mexico is in an area of high seismic activity (Rodriguez-Oreggia et al., 2013), and its geographical position also exposes it to tropical storms. Kovacs et al. (2017) reported several tropical storms and hurricanes, which caused intense rainfall in the Yucatan Peninsula, between 2012 and 2015. Over the period 1980 to 2013, natural disasters such as hurricanes, fires, forest fires, floods, rains, storm surge, droughts, earthquakes, tornados and tsunamis have caused 13,805 deaths and affected 1,839,268 households in Mexico (DesInventar database, n.d.). The majority of these events occurred in the south of Mexico, with

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<sup>4</sup> Guha-Sapir, D., R. Below, and Ph. Hoyois. 2015. *EM-DAT: International Disasters Database*. Prod. Belgium Universite Catholique de Louvain - Brussels.

Veracruz and Oaxaca being the most affected states (DesInventar database, n.d.). The single event that led to the highest number of deaths, 10,000, was the 1985 earthquake in Mexico City. However, frequent small and moderate disaster events, such as floods and droughts, have been shown to affect poverty and human development indicators in Mexico (Rodriguez-Oreggia et al. (2013). Over three decades, from 1970 to 2000, there were 36,851,478 hectares of crops affected by forest fires and droughts; this is equivalent to more than 18 times the total cultivated area in 2000 (CENAPRE, n.d.).

Management of natural disasters needs to address many different aspects of the affected populations, one of these being the impacts on public mental and physical health (Bartlett, 2008; Sastry & Gregory, 2013). There is growing evidence that the breadth and severity of the mental and physical health problems, such as infectious disease outbreaks, malnutrition, morbidity, loss of concentration, depression disorder, or physical impairments, are not limited to the disaster period but continue long after the critical circumstances have finished (Weems & Overstreet, 2008; Furr et al., 2010); (Bartlett, 2008; Du et al., 2010; Sohrabizadeh et al., 2016). Therefore, the development of effective responses through medical facilities and social support relies on the proper assessment of these health impacts (Tunstall et al., 2006; Acierno et al., 2007; Galea et al., 2008; Zhong et al., 2018). Insufficient public healthcare resources may result in deteriorating standards in public health, especially for the most vulnerable groups (Norris et al., 2008; Datar et al., 2013), influencing the ability to restore their well-being and mental health and their preparedness of future disasters, exacerbating social vulnerability and consequently the impact of future disasters (Davis et al., 2010; Roudini et al., 2017).

This study focuses on household experiences of disasters in Mexico, exploring the link between exposure to disasters over a five year period and current physical health status of vulnerable aged-groups (children and elderly). The paper therefore contributes to (i) the studies that analyse the impacts on children's and elderly people's health in the aftermath of natural disasters (Baez & Santos, 2007; Gaire et al., 2016; Adhikari et al., 2017; Labra et al., 2018; Mallett & Etzel, 2018); (ii) the research on natural disasters and health which has focused extensively on mental health (Weems & Overstreet, 2008; Furr et al., 2010) but relatively less on physical health (Bartlett, 2008; Sohrabizadeh et al., 2016). Similar studies that address physical health impacts of disasters on vulnerable age-groups include (Baez & Santos, 2007), who showed that the probability of children being undernourished almost quadrupled, and child labour also increased, in the areas in

Nicaragua hit by Hurricane Mitch. Pörtner (2010) and Datar et al. (2013), showed an association between children's health (e.g. height for age, weight for height, acute respiratory infections and morbidity) and exposure in the last year to small and moderate natural disasters. Labra et al. (2018) illustrated using a qualitative approach the progressive deterioration of elderly people's physical health (hypertension, shingles, physical fatigue, muscle and bone pain, erythroderma and cancer) over a period of four years following their exposure to a major earthquake in Chile in February 2010. In the present study, I take morbidity and physical impairments as indicators of health status, using data collected as part of the official Mexican Household Surveys, which contains questions relating to exposure to, and physical health impacts of, natural disasters at the household level over the last 5 years. Impairment is measured in the American Community Survey (n.d.) through a disability health measure, which incorporates physical incapacity or impairment including limitation of walking, climbing stairs, reaching, lifting or carrying. Morbidity is measured in the same survey as the experience of any individual of having a disease or a symptom of disease, and the period of time over which that person experienced it (Canoy, 2015).

### 4.3. Methods

#### 4.3.1 Model development and data

Econometric estimation of these relationships is based on data acquired from the Survey on the Evaluation of Urban Households (SEUH) within two Mexican social programmes: OPORTUNIDADES and PROSPERA<sup>5</sup>. These contain socioeconomic, demographic, and health information, both at the individual and household level, for the years 2003, 2004 and 2009. The geographical coverage of the analysis is limited to 16 federal entities (Campeche, Chiapas, Colima, Guerrero, Guanajuato, Hidalgo, México, Michoacán, Morelos, Puebla, San Luis Potosí, Sonora, Tabasco, Tamaulipas, Tlaxcala and Veracruz) of the 32 in Mexico, due to data availability. The original data set contains 77,764, 72,421 and 34,034 individual responses for 2003, 2004 and 2009 respectively, for these federal entities included in this study. However, after accounting for missing values, deleting observations that were not in all three surveys, and focusing on the age-relevant groups (infants, adults, elderly), the final panel data set contains 46,848 and 44,718 responses for

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<sup>5</sup> <https://www.gob.mx/prospera>

morbidity and physical incapacity respectively. That is, each year has responses from 15,616 and 14,906 individuals for these two health indicators. According to WHO's age group classification, children are considered in this study those between 2 and 9 years old, adults are aged from 26 to 65, and elderly are those with 66 years onwards, respectively.

The dependent variables, morbidity and physical incapacities, are derived from the SEUH survey, which includes a question about how many days on which family members were sick or experienced health discomfort (measure of morbidity), and how many days they were not able to execute daily activities such as work, help with household chores, going to school, or taking care of the children, due to adverse health issues (measure of physical incapacity) in the previous four weeks. Therefore, answers provided were on a scale from 0 to 28 days.

A number of factors that relate to health status based on the Social Determinants of Health framework (Dahlgren & Whitehead, 1991; WHO, n.d.) and previous studies on the health impacts of natural disasters e.g. (Burton et al., 2009; Pörtner, 2010; Datar et al., 2013) were included in the analysis: access to medical services, education, age and household level income (taking household's income support from the government as proxy of income). It is well-established in the literature, that medical care reduces the level of morbidity, while older adults experience higher levels of morbidity due to the accumulation of chronic conditions with age (Brown, 2018). Similarly, Datar et al. (2013) and Robinette et al. (2017) provide evidence of the effects of access to education and income, showing that morbidity is higher for children of uneducated mothers, and that neighborhoods with higher income are associated with a lower incidence of cardiovascular diseases. Education, income and occupation have all been used to capture the socioeconomic status of people (Marmot, 2004; Brown, 2018) in the context of health. However, income and occupation vary through the life course and so do not capture reliably the long-term influence of socioeconomic conditions on health at the individual level. In contrast, education accumulates through the life course and has been shown to be very strongly associated with health in low-income countries, especially the health of women and children (Nussbaum, 2001; Smith, 2007). Therefore, education, by itself, may be a sufficient proxy to capture the socioeconomic determinants of health at an individual level (Mackenbach et al., 2000; Flanagan & McCartney, 2015). Following this

framework, education and income support from the government were used in this study to capture the socioeconomic status of people.

Information on experience of natural disasters also comes from the SEUH survey, in which individuals were asked whether they or other members of their household living currently or previously in the same house have suffered losses due to natural disasters, such as fires, floods, droughts or any other natural disaster in the last five years. In addition, one may interpret that the latter may include events such as storms, landslides, tropical cyclones, also relatively common in Mexico for the period considered in the data collection (see Table 1 below). The survey also contained a similar question on experience of non-nature related disasters to ensure that the responses to the natural disaster question did not include these non-nature related events, which could have confounded my results. Evidence shows that non-natural disasters, such as major vehicular, industrial accidents, major indoor fires and others, leave people with different types of morbidity, disabilities and physical injuries compared with those arising as a consequence of natural disasters (Lala & Lala, 2006).

#### 4.3.2 Statistical Analysis

A general overview of the main type of natural disasters that occurred over the studied period in Mexico is provided summarizing their frequency, the number of people affected and estimated economic impacts, using the DesInventar database<sup>6</sup>. To explore the link between exposure to natural disasters and current health status, a zero-inflated negative binomial model (ZINB) (Mullahy, 1997; Cameron & Trivedi, 2005), which can account for the preponderance of zeros on the health outcomes or response variables (82% and 92% of respondents reported no symptoms of morbidity and physical incapacity, respectively) and the likelihood of overdispersion, was used. The health indicators data had a potential signal of overdispersion, with an average number of 0.99 days and variance of 3.05 days for morbidity, and average number of 0.4 days and variance of 2.16 days for physical incapacity (figure 4.1). Zero-inflated poisson and negative binomial models were executed and contrasted in order to choose the one that provided the best fit to the data. Thus, the appropriateness of the negative binomial regression as opposed to a poisson model was assessed by using the Likelihood ratio tests. The Young Non-nested

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<sup>6</sup> DesInventar is a nationwide dataset on hazard events at municipal level in Mexico.

Hypothesis provided a test of the zero-inflated model versus the standard negative binomial model.

**Figure 4.1, Histograms of Morbidity, left side, and Physical Incapacity, right side.**

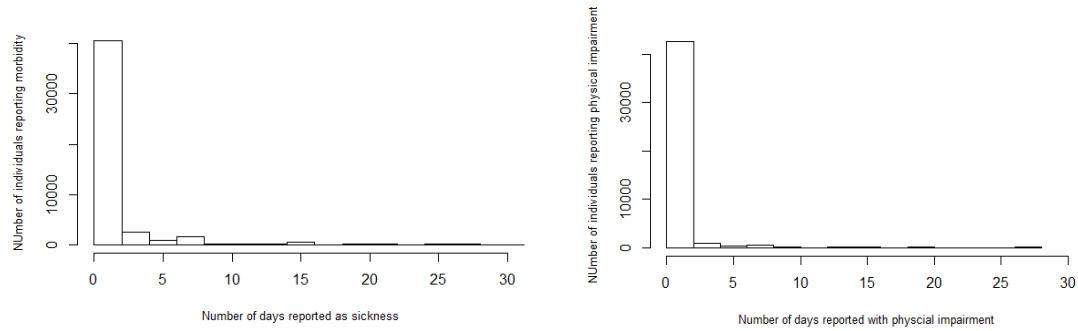


Figure 4.1 shows the frequency of the number of individuals reporting different periods of morbidity and physical incapacity, left and right side, respectively. Source: SEUH, <https://www.gob.mx/prospera>.

The ZINB involves the simultaneous estimation of a negative binomial to model the excess of zeros using the expected health status indicators based on the count data dependent variable (the health outcomes) and a binary, logit, processes. In the logit model, for example, the estimates assess the relation of the regressors with the excess zeroes in the health outcomes variable, for those people that reported not having any morbidity or physical incapacity. Therefore, the ZINB distribution is a mixture of distributions, which model the probability of a zero value and the probability of a positive count. The negative binomial probability function as a form of modeling the positive count is giving by the following expression:

$$P(y = k) = \frac{\Gamma(\alpha+k)}{\Gamma(\alpha)\Gamma(k+1)} \left(\frac{\alpha}{\alpha+\lambda}\right)^\alpha \left(\frac{\lambda}{\alpha+\lambda}\right)^k \quad (1)$$

where  $k$ ,  $\lambda$ ,  $\alpha$  represent the count data, the health outcomes mean and the dispersion estimator. The expected value of the dependent variable is giving by:

$$E(y) = \lambda = \exp(X\beta)$$

Where,  $y$  represents the health dependent variables, morbidity and physical incapacity.

If I incorporate the binomial part function (via logit link) in the negative binomial probability function, then the ZINB model is:



$$P(y = 0) = \phi + (1 - \phi) \left( \frac{\lambda + \alpha}{\alpha + \lambda} \right)^\alpha$$

$$P(y = k) = (1 - \phi) \frac{\Gamma(\alpha + k)}{\Gamma(\alpha)\Gamma(k+1)} \left( \frac{\alpha}{\alpha + \lambda} \right)^\alpha \left( \frac{\lambda}{\alpha + \lambda} \right)^k \text{ for } k=1, 2, \dots \quad (2)$$

In both models, the probability of a zero value is represented by  $\phi$ . Thus, the overall probability of a zero value is the sum of  $\phi$  and the probability of a zero value from the negative binomial function with a probability of  $(1 - \phi)$ . Whereas, the probability of positive counts, greater than 0, is the product of  $(1 - \phi)$  and the probability of a positive value of the negative binomial model.

The ZINB regression model, for the count component then is:

$$\log(\lambda_i) = X_i\beta \text{ and } \text{logit}(\phi_i) = Z_i\gamma \quad (3)$$

Where  $X_i$  and  $Z_i$  are the vectors of covariates of the  $i$ th individual, and  $\beta$  and  $\gamma$  are the corresponding vectors of the regression coefficients respectively. In this case, I regress the same covariates for both models, the binomial which use the logit distribution and the negative binomial for the account part, for assessing the effect of the regressors on both models. However, note that in the results part I just present the results for the count part model because my interest of measure the effect of the regressors on the level of morbidity and physical incapacity. Therefore, the vectors  $X_i$  and  $Z_i$  are the same, for simplicity I use just the vector  $X_i$  which contains the following variables:

$$X_i = (\text{children, elderly, education, access to medical service, income support from the government, experience to non - nature related disasters, Natural Disasters * children, Natural Disasters * elderly})$$

The vector of covariates includes age groups (children and elderly dummy variables), dummy variables that capture if individual has at least completed primary education, access to medical service, and dummy variables related to whether an individual reports that his/her household receive income support from the government. Finally, a dummy variable represents whether the individual has experienced non-nature related disasters. Interaction terms were used to test the hypothesis that children and elderly are associated with natural disasters with respect to the adult population. Thus, *Natural Disasters \**

*children* indicates the children who faced natural disasters and *Natural Disasters \* elderly* refers to the elderly people who experienced natural disasters. Finally, the ZINB log-likelihood, giving the observed data, is estimated combining the previous expression, (3), with the equation (2).

The above elaboration was modified to consider a fixed effect process in order to control for the unobserved municipalities' time-invariant characteristics such as customs, traditions, beliefs of the community, public safety and culture that have been shown to influence human health (WHO, n.d). The fact that each municipality has their own festivals or social events, many related to food culture, makes it a suitable spatial unit to capture these determinants. This means the ZINB model includes dummy variables that act as intercept shifters to account for the potential unobserved heterogeneity, at the municipality level, that may have an effect on the health outcomes. Following this idea, variation in morbidity and physical health, that can occur across the temporal dimension, was modeled by adding time fixed effects. The model was estimated in R using the `zeroinfl()` function in the `pscl` package (Zeileis et al., 2008).

#### 4.4 Results

Table 4.1 describes the type of natural disaster, its frequency, affected people, and the economic value lost in the studied area from 2000 to 2009<sup>7</sup>. Forest fires, storms, droughts, floods and tropical cyclones were the events with the higher number of records, resulting in a total of 254 events. Tropical cyclones, earthquakes and droughts affected a higher number of people: 1,157,345, 505,385 and 175,103 people, respectively. The natural disasters that caused the highest economic impacts were tropical cyclones, floods and droughts.

**Table 4.1**, Description of Natural Disasters in the studied area, from 2000 to 2009.

<b>Type of natural disaster</b>	<b>Frequency</b>	<b>Deaths</b>	<b>Affected People</b>	<b>Loss in US millions of dollars</b>
Forest fire	59	9	92	121.14

<sup>7</sup> The cover period from the first survey until the last one is from 1998 to 2009. However, table 4.1 only describes natural disasters events from 2000 due to the fact data the CENAPRED only contains information from this year (<https://www.gob.mx/cenapred>)

Storm	59	38	35,125	3.94
Drought	48	0	175,103	207.55
Flood	45	33	73,103	468.86
Tropical cyclone	43	130	1,157,345	2491.93
Landslide	30	78	3,489	6.26
Earthquake	8	25	505,385	109.19
Heat waves	5	5	5	0
Volcanic activity	2	0	41,216	12.23

Source: Centro Nacional de Prevención de Desastres (CENAPRED, n.d).

Table 4.2 illustrates the descriptive statistics for morbidity and physical incapacity. It also shows the proportion of natural disasters and the control variables with respect to the total population. There is a small proportion of people, around 5%, who faced natural disasters; a higher proportion, 22%, suffered other disasters (not natural). Less than half of the population has access to medical services (41%) and more than half of the population receives support from the government, 69%.

**Table 4.2,** Description and descriptive statistics of the responses and covariates.

<b>Variables</b>	<b>Description and type of variable</b>	<b>Mean (SD)*</b>	<b>Median (max, min)</b>
Morbidity	In the last 4 weeks, how many days were you sick	0.99 (3.05)	0 (0, 28)

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or experienced health discomfort?

*Count variable.*

Physical incapacity	In the last 4 weeks, how many days you were not able to execute the following daily activities such as: work, household chores, going to school, taking care of the children, etc. because of health issues?	0.4 (2.17)	0 (0,28)
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*Count variable*

<b>Variables</b>	<b>Description and type of variable</b>	<b>Proportion with respect of the total morbidity</b>	<b>Proportion with respect of the total physical incapacity</b>
Faced Disasters	Natural In the last 5 years, has this house suffered any loss due to fire, flood, drought or any other natural disaster including loss or damage to any good that belonged to any person who lives or lived here, in this house? Yes (=1)/No(=0)	5%	4.6%

*Dummy variable*

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**Control variables<sup>1</sup>**

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Children	<i>Dummy variable</i>	28%	27%
Elderly	<i>Dummy variable</i>	8%	9%
With Education	<i>Dummy variable</i>	93%	95%
With access to medical service	<i>Dummy variable</i>	41%	41%
With income support of the government	<i>Dummy variable</i>	70%	69%
Faced non-nature related disasters	<i>Dummy variable</i>	22%	22%

Source: ENCELURB ([https://evaluacion.prospera.gob.mx/es/eval\\_cuant/p\\_bases\\_cuanti.php](https://evaluacion.prospera.gob.mx/es/eval_cuant/p_bases_cuanti.php))

Note: The total number of observations for morbidity and physical contains 46,848 and 44,718 individual responses.

<sup>2</sup> For dummy variables, 1=presence of the group or the mentioned characteristic, 0=absent of the group or the mentioned characteristic

Table 4.3 shows the estimates of ZINB for morbidity and physical incapacity for my groups of interest, children and elderly; controlling for socioeconomic and demographic factors. The overdispersion parameter was found to be significantly different than zero, and the likelihood ratio test also rejects the null hypothesis of overdispersion (LR=20,413 and LR=8788.5, for morbidity and physical incapacity, respectively p-value>0.000). In addition, the values of Voung Hypothesis confirm that the binomial inflated model fit better the data than standard negative binominal (V=31.57 and V=13.54, for morbidity and physical incapacity, respectively, p-value <0.000). The coefficient on the effect of natural disasters in the adult population's health count indicators were negative and not statistically significant. In relation to the vulnerable age groups, the interactions of elderly and children with natural disasters were positive and significant (p-value<0.01) in the

morbidity count model. This means that the relation between natural disasters and morbidity counts varies for different age groups; i.e., it indicates that children and elderly people who have experienced natural disasters are more likely to be sick or report a worse level of current health discomfort than non-elderly adults who have experienced natural disasters. The coefficients presented in table 4.3 are in the form of ‘log-odds’. Therefore, having their exponential form, they can be interpreted as odds ratios. For elderly (children) that experienced natural disasters in the last 5 years, the likelihood of their experiencing a current worse morbidity outcome than those in the same group age who had not experienced natural disasters is about 48% (17%). The relevant values are the odds ratios of 1.47 and 1.17, which are the exponential of 0.39 (this is,  $-0.038+0.428$ ) and 0.159 (this is,  $-0.038+0.197$ ) respectively. Of people who have experienced disasters, elderly people are 53% (odds ratio is 1.53, exponential form of 0.428, interaction coefficient) more likely, and children 22% more likely, to report higher levels of sickness than non-elderly adults. Thus, natural disasters seem to have a stronger adverse effect on the morbidity of children and elderly people compared with adults.

The interaction of elderly people and natural disasters was also positive and significant (p-value <0.05) for the case of physical incapacity, indicating that it is expected that among those that have faced natural disasters, elderly people were more likely to experience more days with symptoms of physical incapacity than was the case for adults. The probability of elderly people who experienced natural disasters reporting a higher number of days experiencing physical incapacity compared with adults who had also experienced disasters was 75% (odds ratio of 1.75, which is the exponential form of 0.56). With respect to children, the interaction term was positive but not statistically significant.

**Table 4.3:** Log-odds regression estimates, of the zero-inflated negative binomial, assessing the relation of morbidity (centre column) and physical incapacity (right column) with natural disasters and their interactions with different age groups (children, elderly and adults), for the count and zero-inflated models. Standard errors are provided in parenthesis.

VARIABLE	MORBIDITY	PHYSICAL INCAPACITY
	Zero-inflated negative binomial	Zero-inflated negative binomial
With education	0.18 ***	0.1

	(0.046)	(0.109)
With medical service	-0.044	0.04
	(0.023)	(0.046)
With income support of the government	-0.042	0.02
	(0.025)	(0.049)
Non-natural disasters	0.064 **	0.09
	(0.025)	(0.048)
Natural Disasters	-0.038	-0.09
	(0.053)	(0.102)
Children	-0.329 ***	-0.48 ***
	(0.027)	(0.056)
Elderly	-0.334 ***	-0.4 ***
	(0.048)	(0.092)
N.D:Children <sup>1</sup>	0.197 *	0.18
	(0.1)	(0.18)
N.D:elderly <sup>2</sup>	0.428 *	0.56
	(0.197)	(0.341)
Log(theta)	0.128 ***	-0.48 ***
	(0.009)	(0.01)

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Note: p-value <0.0001'\*\*\*'; p-value <0.001 '\*\*\*'; p-value <0.01 '\*'; p-value <0.05 '.'

<sup>1</sup>This denotes the interaction between self-reported experience of natural disasters and children.

<sup>2</sup>This denotes the interaction between self-reported experience of natural disasters and elderly people.

Access to medical services and financial-support from the government were statistically significant and negatively related with the morbidity counts. Moreover, self-reported

experience of other non-natural disasters was significantly and positively associated with morbidity. However, these factors were not significant for the physical incapacity counts. Finally, the effect of having completed at least primary education was positively related to the number of days respondent had experienced morbidity.

#### 4.5 Discussion

This chapter has examined the relationship between self-reported morbidity and physical incapacity of vulnerable age groups, children and the elderly, with having experienced natural disasters in the last five years. To the best of my knowledge, this is the first study to explore the association of natural disasters with the health of children and elderly people in Mexico. The analysis showed that children and elderly people who have experienced natural disasters are more likely to suffer morbidity and incapacity than non-elderly adults who have also experienced natural disasters. It is therefore very likely that among those exposed to natural disasters, children and the elderly experienced higher than average level of sickness in the five years following disasters. The probabilities of higher morbidity counts for elderly people and children relative to non-elderly adults were 53% and 22% respectively. These findings are consistent with other studies (Burton et al., 2009; Datar et al., 2013). For instance, Datar et al. (2013) showed that disasters can raise the probability of acute illness in children by 9-18% in rural areas in India. Burton et al. (2009) found that the level of morbidity for elderly people increased about 13% after the Hurricane Katrina, in a cohort study of people enrolled in a Managed Care Organization in New Orleans. Results are also consistent with other literature on the deterioration on health, using other health outcomes, of children and elderly people as a result of exposure to natural disasters (Tyler & Hoyt, 2000; Pörtner, 2010; Gaire et al., 2016; Labra et al., 2018). Elderly people who had been exposed to disasters also reported higher levels of physical impairment over the last five years compared with non-elderly adults. The odds of elderly people experiencing physical incapacity in the five years following a disaster were 75% higher than adults who have experienced natural disasters. This contrasts with the findings of Sastry and Gregory (2013), who found no relationship between elderly people and increasing disabilities (walking, climbing stairs, reaching, lifting or carrying) in New Orleans following hurricane Katrina. Although the focus of this analysis was to investigate the association of natural disasters on the physical health of children and elderly physical. The results also highlighted the role of access to medical



services and income in reducing adverse health outcomes ,which is consistent with much previous work (Robinette et al., 2017; Brown, 2018).

There are several methodological issues relating to the survey, that need to be taken into account in relation to the results and analysis presented. First, the data did not provide further information on precisely when the respondents experienced the natural disasters, which could be any time in the previous five years. Thus, it is not possible to be sure whether the incapacity or morbidity referred to occurred during or in the immediate aftermath of the disaster, or whether it occurred much later. Secondly, in common with other studies which use surveys in the context of natural disasters (Chiu et al., 2002; Sastry & Gregory, 2013; Lohmann & Lechtenfeld, 2015), the survey used information on morbidity, physical incapacity and natural disasters which was self-reported and mainly based on the individual's long-term memory, which may result in some bias. The directionality of this bias overall is not possible to determine, although the large number of interviews in this study may reduce this level of bias (Yamane, 1973). Finally, this study has also attempted to establish associations rather than cause and effect between natural disasters and health outcomes. Other determinants of health such as housing conditions, public infrastructure, habits, diet or social and community networks may play an important role in affecting people's health (Dahlgren & Whitehead, 1991), but these could not be included due to lack of available data.

Despite these potential shortcomings, this study provides the advantage, unlike previous research in this area, of accounting for unobserved heterogeneity, which was possible because of the good resolution of the study, being conducted at the municipality level. The World Health Organization (WHO, n.d.) establishes the importance of this heterogeneity in the variety in social health determinants at the municipal level (such as customs and traditions). Lastly, my data come from surveys which provide direct information on self-reported impacts, and thus allow the experience of disasters on households to be captured more precisely than many other sources of data (Karim, 2018).

At the policy level, previous literature has shown the importance of social support through public programmes for mitigating the negative health impacts of natural disasters (Chiu et al., 2002; Baez & Santos, 2007). My results indicated that children and elderly people who have access to medical services experience lower levels of morbidity. Only 41% of those interviewed had access to medical services. Therefore, extending the quality and

service of health care, especially for children and the elderly, would be expected to reduce the impact of natural disasters on morbidity. Moreover, social programmes aimed to monitor the physical health status of children and elderly people following disasters, combined with appropriate treatment where necessary, could mitigate the negative impact on their health. Within these social programmes, there is a need to design specific targeted elements for vulnerable groups, so that they can prepare more effectively for disasters and be better equipped to mitigate the adverse health effects when disasters occur (Baez & Santos, 2007). For instance, some factors such as social isolation or living alone may exacerbate the adverse health impacts of natural disasters for elderly people (Knowles & Garrison, 2006; Labra et al., 2018). Programmes that are targeted at those most in need, but look beyond natural disasters to the wider determinants of health and seek to build community capacity in a broad sense, would be those that are likely to deliver the greatest dividends in reduced morbidity and physical incapacity due to natural disasters, in both children and the elderly.

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## Chapter 5: Discussion, policy implications and suggestions for future research.

Evidence from research, especially when informed by knowledge of the local context, is a powerful instrument to inform public policy options and decision-making (McLaughlin et al., 2007; Head, 2010). In the case of environmental justice, understanding the differences in the local context that underlie unequal exposures to environmental hazards is key to designing policy strategies for local governments (Insaf & Talbot, 2016). The challenge faced by policy-makers is to identify and assess the multiple social interventions which can help to reduce adverse health outcomes of environmental hazards on the health of people, particularly where levels of exposure or impacts are concentrated on vulnerable social groups (Kousky, 2016).

The aim of the present study was to provide evidence on the impact of environmental and socioeconomic determinants of human health on vulnerable groups in Mexico. It showed that people living in adverse socioeconomic conditions are more exposed to air pollution and more prone to higher health risks, including those emerging from natural disasters. Vulnerable groups, children and elderly people, and those with low income and education levels, and without medical services and financial support from the government are affected by issues of environmental and health justices. The thesis also identified hotspot areas in Mexico City and surrounding municipalities where environmental hazards (air pollution), and health risks (newborns with low birth weight) are highest.

In chapter 2, I evaluated the existence of environmental justice in exposure to air pollution in Mexico City, by testing whether communities in deprived economic conditions and vulnerable age groups (children and elderly) in Mexico City are exposed to higher levels of ozone and PM<sub>10</sub>. The approach taken allowed me to investigate these environmental justice issues for those hotspots where there are higher levels of air pollution, and therefore where the risk to human health is greater than in areas with lower concentrations of pollutants. In chapter 3, I assessed the risk of low birth weight in Greater Mexico City, as an indicator of children's health, through a spatial analysis of the temporal evolution of the levels of TLBW risk across the different municipalities. Understanding the spatio-temporal dynamics of TLBW is important for developing strategic policies for TLBW risk reduction, which can then focus on those municipalities with high and growing risk. Quantifying the influence of socioeconomic status of mothers on TLBW risk provided

further information relevant to the potential role of public policy interventions. In chapter 4, I explored the effect of natural disasters on physical health inequalities, evaluating the potential medium- to long-term consequences of exposure to natural disasters on people's health, with particular attention to vulnerable age groups (children and elderly). Results of this work support the need to develop post-disaster policies that reduce disparities in health outcomes following exposure to natural disasters.

The main findings of this research are discussed further in this chapter, alongside the implications for public health policy, especially in relation to the patterning of environmental hazards and those social groups at higher risk of adverse health outcomes.

### 5.1 Summary of main findings.

The main contributions of this thesis may be grouped into four categories as follows:

- (a) Environmental injustice is prevalent in Mexico City, with detrimental health impacts greater for poorer socioeconomic communities which experience higher levels of air pollution.
- (b) Elderly people and children bear a disproportionate burden of environmental health risks from air pollution and natural disasters.
- (c) There are hotspots (cluster of municipalities) in the north of Mexico City and surrounding areas where environmental and health inequalities co-exist.
- (d) There are opportunities for policy-makers in Mexico City to use education, medical and financial support measures to better protect vulnerable citizens from environmental and health risks.

**(a) Environmental injustice is prevalent in Mexico City, with detrimental health impacts greater for poorer socioeconomic communities which experience higher levels of air pollution.**

Socio-economic deprivation has been linked to poor health status, with low socio-economic status being a risk factor for ill health and early death (Pickett & Pearl, 2001; Roux & Mair, 2010; WHO, n.d. a). This may be related to the fact that the poor people are more vulnerable to unhealthy diets and have limited access to medical facilities. This link between poverty and ill health makes reducing extreme poverty a major policy priority which is aligned with the first sustainable development goal (SDG) (Prüss-Üstün and Neira (2016).



Neighborhoods in Mexico City with greater socio-economic deprivation were found to be more exposed to PM<sub>10</sub> pollution compared with wealthier social groups. Moreover, the association between economic status and exposure to PM<sub>10</sub> was stronger at locations where the levels of PM<sub>10</sub> were the highest within the City (figure 2.1a, 2.1c and 2.2, and table 2.4a). This means that ***the evidence for environmental injustice is actually stronger in neighbourhoods with the highest levels of PM<sub>10</sub>***. Given that in Mexico City, the areas with high levels of PM<sub>10</sub> often exceeded the thresholds recommended by WHO to avoid health risks (WHO, 2006), these results further suggest that ***those people with the lowest socioeconomic status are more likely to face adverse health impacts as a consequence of to their differential (higher) exposure to PM<sub>10</sub>, and thus environmental and health injustice are linked***. These findings are consistent with work in England, the Netherlands and the U.S. where the distribution of air pollution results in a disproportionate respiratory health risk for those living in the most deprived neighborhoods (Briggs et al., 2008; Hajat et al., 2013; Fecht et al., 2015). Moreover, the findings of this chapter add to this literature, showing that ***the relationship between low socioeconomic-status and air pollution varies across quantiles of PM<sub>10</sub> levels, and that it is stronger at locations with higher pollution levels***. In fact, the magnitude of this association at various air-pollution levels differs considerably from the OLS coefficient (estimated for the PM<sub>10</sub> mean value), illustrating the benefits of the approach used in this chapter.

***(b) Elderly people and children bear a disproportionate burden of environmental health risks from air pollution and natural disasters.***

Previous research has shown that between 24% and 26% of deaths of mature adults (between 50 and 75 years old) are attributable to environmental hazards, including air pollution (Prüss-Üstün & Neira, 2016). In fact, elderly people are more likely to suffer from health inequality, as they are more susceptible to acquire or develop noncommunicable diseases (especially cardiovascular diseases) and different injuries through high exposure to air pollution (Kovats & Kristie, 2006; Rosenkoetter et al., 2007; Prüss-Üstün & Neira, 2016). My analysis has shown that ***in Mexico City, the elderly population is disproportionately exposed to air pollution, in particular PM<sub>10</sub>***. In fact, ***policy attention is needed to address this inequality in the locations within this city with elevated levels of this pollutant*** (and therefore where health risks are higher). Overall, my results are consistent with studies in the US (Texas, New York, Michigan, and Wisconsin)

by Zou et al. (2014) and Clark et al. (2014), which showed, respectively, that senior people tend to be residing in areas with elevated levels of SO<sub>2</sub> and NO<sub>2</sub>. However, this pattern is not universal. For example, it was not the case in Montreal, where elderly people did not suffer any environmental injustice, i.e., they were not disproportionately exposed to air pollution (PM<sub>2.5</sub>) (Carrier et al., 2014).

Similarly, there is considerable evidence on the negative effects of air pollution on the health of children due to their biophysical conditions (Barouki et al., 2012; Kousky, 2016; Prüss-Üstün & Neira, 2016; Drisse & Goldizen, 2017). Previous studies have shown that one third of the global burden of disease in children is due to environmental hazards (including air pollution), compared with one quarter for adults (Prüss-Üstün & Corvalán, 2006). Air pollution can affect the proper development of children's organs and systems (Bobak, 2000; Schwartz, 2004; Drisse & Goldizen, 2017). *In the case study of Mexico City, my results illustrate that communities with a high percentage of children seem to be more exposed to ozone.* The spatial analysis identified coincidence between high levels of ozone (see figure 2.1b) and some clusters of high proportions of children (see figure 2.1d) in the south of Mexico City. This finding complements some previous literature, which has presented evidence on the unequal exposure to air pollution of children, the extent of inequality depending on the local context and type of pollutant (Hajat et al., 2015).

My analysis in chapter 4 showed that elderly people and children who have suffered recurrent natural disasters are more likely to be at risk of worsening morbidity status than adults; and elderly groups are also at higher risk of a deteriorating physical capacity (table 4.3). Thus, **children and elderly groups are likely to be especially vulnerable to the increasing frequency of natural disasters** (Datar et al., 2013; Labra et al., 2018), because their health can deteriorate beyond the immediate impact of such events. Moreover, even though natural disasters may affect a large number of people due to their large scale and frequency (Pörtner, 2010; Datar et al., 2013), elderly people tend to be especially vulnerable to these events due to factors such as living alone, social isolation, inadequate air conditioning systems, and other housing characteristics (Knowles & Garrison, 2006; Kovats & Kristie, 2006). Previous evidence is aligned with the findings of the work in this thesis. Burton et al. (2009), Labra et al. (2018) and Tyler and Hoyt (2000) also concluded that senior people worsened their health status (morbidity, hypertension, physical fatigue) after experiencing natural disasters such as hurricanes,

earthquakes and flooding in Chile, New Orleans and Iowa (US) respectively. In the case of children, their vulnerability is partly driven by having a less mature immune system. They also depend on their parents, who can be overwhelmed, unprepared or see their income and consumption possibility drastically reduced (affecting nutrients and vitamins intake); children may also be separated from their parents (Kousky, 2016; Drisse & Goldizen, 2017). The impact of these events on children is therefore a concern at the international scale, with literature showing evidence that floods, droughts and earthquakes can all affect children's height, weight, level of stunting and morbidity state (Pörtner, 2010; Datar et al., 2013; Rydberg et al., 2015).

**(c) There is a hotspot (cluster of municipalities) in the north of Mexico City where environmental and health inequalities co-exist.**

Identifying areas where environmental and health inequalities occur provides valuable information at the policy level in order to develop programmes and measures to deal with these inequalities (Chaix et al., 2006; Ugarte et al., 2015). Researchers are increasingly using spatial analysis to provide this information. For instance, (Chaix et al., 2006) identified eight clusters of children with lower socioeconomic condition who were disproportionately exposed to air pollution in Malmo, Sweden. More recently, (Clark et al., 2014) identified that in the US there is environmental inequality in the east area of the country (New York, Michigan, and Wisconsin); while there is evidence that East European countries, with lower socioeconomic status, are more exposed to air pollution than West European countries (Richardson et al., 2013).

The spatial analysis in chapter 2 illustrated the existence, in the northern part of Mexico City, of hotspots of socially vulnerable groups who suffer unequal exposure to air pollution. This part of the city includes municipalities where people with deprived conditions face high levels of PM<sub>10</sub> (figure 2.1a and 2.1c). This area of the city is host to many industries and main roads (Air Quality in Mexico City, annual report 2014), and the emissions from vehicles and industries are the principal source of particulate matter in Mexico City (Querol et al., 2008). This hotspot area in the north has become heavily built-up as a result of government incentives to industry and housing, alongside the availability of proper infrastructure (Cruz & Garza, 2014). Municipalities within this hotspot such as Gustavo A. Madero have been recognized previously as localities with

the greatest concentration of people in poverty in Mexico City, where people walk long distances to take crowded public transport or work on the street, increasing their exposure to PM<sub>10</sub> (Calderón-Garcidueñas & Torres-Jardón, 2012; CONEVAL, n.d.).

Similarly, the results of chapter 3 also identified municipalities where there is a combination of socioeconomic deprivation and an increasing trend of higher risk of infants with low birth weight. This analysis focused on Greater Mexico City, a larger area considered in chapter 2, and showed that **municipalities with higher risk of TLBW occurred mainly in the south and west of this city**, with just one high risk municipality in the north. However, the findings of this chapter also show that most of these municipalities present a stable dynamic over the last eight years with respect to the risk level of TLBW. The analysis detects **two municipalities, Melchor Ocampo and Benito Juárez, as having an increasing pattern of TLBW risk compared with the overall trend** (figure 3.3a). Moreover, **there are 10 municipalities, mainly located in the north, which have a relatively low TLBW risk, but which need policy attention because they also present an increasing trend of TLBW risk during the study period** (figure 3.3b and figure 3.3c). As mentioned above, this northern part of Mexico City has high concentrations of industry, transport and pollution, which may increase the risk of having a child with low birth weight. Moreover, **the north of Greater Mexico City, seems to represent a hotspot for health inequalities**, because is also characterized by low levels of income and education.

**(d) There are opportunities for policy-makers in Mexico City to use education, medical and financial support measures to better protect vulnerable citizens from environmental and health risks.**

Mexican City's policy makers need to evaluate and implement policy options to reduce the health inequalities cause by unequal air pollution exposure for those with socioeconomic disadvantage. Work in chapters 3 and 4 has highlighted possible roles that the government could play in remediating the effects of health inequalities. In chapter 3, I showed that *governmental support to facilitate access to education to women may reduce the risk to TLBW in new born infants in Mexico City* (table 3.1). This outcome is not new in the literature, Young et al. (2010) and Luo et al. (2006) also found that low education level is a factor which can trigger the risk of having children with low birth

weight in studies carried out in U.S and Canada, respectively. Moreover, chapter 4 informs policy-making by providing evidence on the role that *facilitating access to medical services and offering financial-support to vulnerable groups can have in mitigating the level of sickness, morbidity, to those experiencing from natural disasters* (table 4.3). The WHO (n.d. b) has consistently indicated that people with medical care may have better health outcomes, and Dahlgren and Whitehead (1991) also showed the positive effect of government financial support on health of people. This thesis has advanced on this issue, by exploring the role of the government in reducing the unequal distribution of medium/long term health consequences of natural disasters.

## 5.2 Policy implications

My quantitative analysis of the evidence on the human health risk associated with environmental hazards and deprived economic conditions has allowed me to propose some policy implications in each of the chapters. The following section represents a summary of these policy implications that have emerged from the key findings of the thesis.

Environmental injustice occurs when a community with low socio-economic status experiences a disproportionately high exposure to air pollution (Havard et al., 2009; Hajat et al., 2015). Therefore, policy actions needed in order to reduce environmental injustice can involve: (i) improving economic conditions for the vulnerable communities, through mechanisms such as tax relief, subsidized education, income support programmes and job promotion; (ii) reducing air pollution at locations where these communities live; and/or (iii) facilitating the resources that could increase the ability of the affected citizens to mitigate their health risk (e.g. having better air ventilation at home or work).

The findings of this research support the need for actions to be taken in relation to the first policy option, both in relation to TLBW risk and air pollution. This is, to provide basic medical facilities, facilitate access to education, and provide financial support to address health injustices. For the case of air pollution, it should be highlighted that these policy measures might not be sustainable in the long period without a decline in the levels of air pollution. In this sense, in Mexico City, given that industries and commuter traffic are two of the main sources of PM<sub>10</sub> and ozone, measures and programmes should be implemented to better regulate the pollution emissions from industries, as well as

promoting reduced use of vehicles through more efficient public transport, particularly in the north (to protect elderly) and in the south (to protect children). These measures would thus contribute to resolving inequalities of environmental hazards suffered in the hotspot municipalities of Azcapotzalco. Similarly, policies that contribute to traffic reduction will benefit elderly people living in the municipalities of Cuauhtémoc and Miguel Hidalgo (also within the identified hotspot), which experience the highest road density and dense traffic.

The analysis carried out in this thesis also supports recommendations for programmes that reinforce the monitoring of adverse health outcomes in the medium to long term, i.e., beyond the immediate effects of natural disasters. The findings of chapter 4 showed that children and senior people are impacted in their health (morbidity or/and physical incapacity) by different and recurrent natural disasters beyond the impacts that occur immediately after these events. Monitoring health trends should be of paramount importance for policy makers to allow for early interventions in dealing with the health effects of natural disasters, through primary health care, as efficiently as possible. This can contribute to reduce the need for more expensive treatment that can occur if degradation in health status is left unattended (WHO, n.d. a).

Furthermore, a more novel approach to address the long-term effects of natural disasters on human health could be developed by reinforcing the resilience of vulnerable communities. There is already some evidence that strengthening the resilience capacity of communities following natural disasters can help to mitigate the negative impact on health of such events (Garcia & Sheehan, 2016; Salazar et al., 2016). Programmes to build resilience capacity could promote mental health preparedness to deal with these post-effect disaster events, particularly of children and elderly people. In Japan, there are already a variety of mental health programmes which aim to deal with the post-effect of earthquakes properly in order to mitigate its negative health effect (Kozu & Homma, 2014).

In the case of elderly people, given that some factors such as social isolation or living alone have a negative influence on their health after experiencing these events (Knowles & Garrison, 2006; Labra et al., 2018), programmes could be implemented to avoid these aspects, building social networks, promoting social interaction, and increasing the sense of belonging in the communities. All these activities would support the health of this

vulnerable group, improving their resilience and ability to recover their health in a shorter period of time.

### 5.3 Further research

Some recommendations emerge from this thesis for future research which may help to increase understanding of the impact of environmental and socioeconomic factors on people's health.

*Investigate other socioeconomic determinants of health.* Recent studies have emphasized the need to explore the impact of other health determinants, such as the layer of major structural environment or social and community networks (defined previously), at individual or at the macro level (Miao et al., 2015; Rathmann et al., 2015). For instance, WHO (n.d. b) and Dahlgren and Whitehead (1991) have emphasized the effect of social and community networks or social support network on health of people respectively. Therefore, investigating other determinants of socioeconomic determinants which drive the health of people, especially for vulnerable groups, may provide additional insights into how to mitigate the impact of natural hazards. For instance, one potential area of study is the role of social networks in the context of reducing the effect of environmental hazards on health for children and elderly people. Vulnerable groups require the assistance of the other members of their family. The health of elderly people is at risk of deteriorating following exposure to natural disasters due to social isolation, disruption of family ties or the lack of partners (especially for elderly women) (Kovats & Kristie, 2006; Burton et al., 2009; Ergin & Mandiracioglu, 2015). Elderly people need the assistance of their family to take care their own health. Whereas, children require the economic support of their families to get involve with their schooling activities. Therefore, in the Mexican context, it is likely that elderly people and children would be less affected by the exposure of natural disasters if the social networks were stronger.

*Examine the factors which created the conditions of living in areas which are more prone to natural disasters or to the burden of air pollution.* It is relevant to identify the historical, economic and social contexts which have given rise to these local conditions (Hajat et al., 2015). For instance, poor communities are likely to reside in cheaper housing due to their economic conditions. At the same time, industrial areas are more commonly established

in cheap lands (Saha & Mohai, 2005; Mohai et al., 2009). As a consequence, there is a relationship between housing, of people with lower SES, and industrial development. To identify the root causes of these association would require the use of longitudinal data. This would allow the identification of particular historical forces such as residential segregation and uneven urban-industrial development (Brulle & Pellow, 2006; Mohai et al., 2009) that may have led to unequal exposures to air pollution or natural disasters which impact negatively on the health of people. An understanding of these factors may enable the development of social policies that are more effective in reducing the environmental inequality of vulnerable groups.

*Explore new living patterns of people to deal with high levels of pollution or/and natural disasters.* Recently there has been an increasing frequency of extreme natural events (Baez & Santos, 2007; Guha-Sapir et al., 2017), and this trend is likely to continue into the future. Kousky (2016) has suggested that communities that are prone to frequent natural events may be more effective at developing strategies to deal with these events. An analysis of such strategies may provide useful insights into the most effective ways to reduce the impact of frequent and repeated natural events on people's health. For instance, Bangladesh has implemented the use of boats to enable children to continue to attend school in the event of flooding (Kousky, 2016). Likewise, it would be interesting to explore new living patterns to deal with natural hazards or elevated levels of pollution in a healthy way without the interruption of the daily activities of people. In the Mexican context, research could investigate how new equipment or practices, such as the use of breathing masks or the use of boats, to deal with higher levels of air pollution or a flooding respectively, could mitigate the adverse consequences of these events and bring health benefits to people exposed to them.



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## Appendices

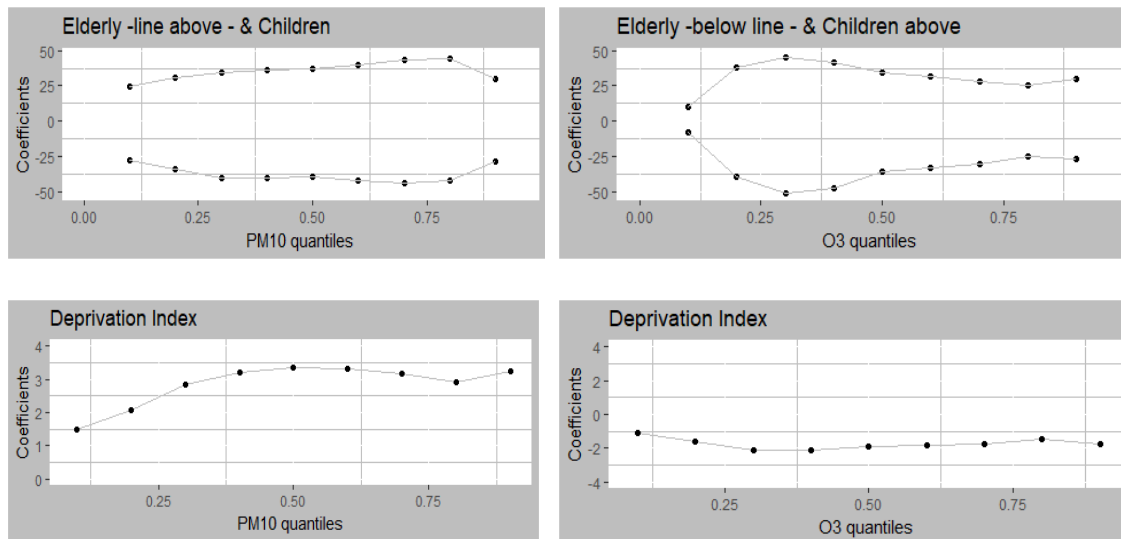
Appendix A: Chapter 2, Monitoring stations and spatial quantiles results with standard errors.



**Figure 2.A1a:** PM<sub>10</sub> monitoring stations across urban AGEBs in Mexico City in 2015.

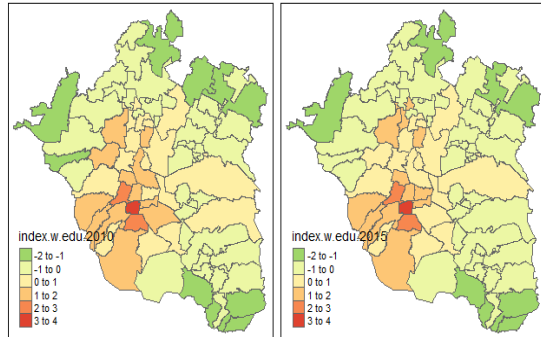


**Figure 2.A1b:** Ozone monitoring stations across urban AGEBs in Mexico City in 2015.



**Figure 2.A2:** Spatial quantile regressions with different quantiles of PM<sub>10</sub> (left) and ozone (right) as response variables, controlling for the standard errors from the kriging interpolation. These figures show the coefficients of elderly, children and deprivation index with the different quantiles of PM<sub>10</sub> and ozone (each dot represents a percentage quantile from 10% to 90%).

**Figure 3.B1.** Spatial distribution of economic and education index, for 2010 and 2015 years.



The figure displays the economic and education index across Greater Mexico, for 2010 and 2015 years. The green and red colors show the municipalities with worse and better conditions in these issues respectively.