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Effect of air pollution on morbidity in Sweden
- county-level case study

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Abstract

Many studies on air pollution have been done on mortality, morbidity and hospital admissions. Little has been done on air pollution and selected air pollution-related morbidities. This research tried to fill this gap. In this research, I study the effect of air pollution on the number of total patients per 100K inhabitants on the 21 Swedish counties. I selected 4 air pollutants mainly: sulphur oxides, particulate matter 2.5μg/m^3, particulate matter 10μg/m^3 and total suspended particulate; and 11 diseases that are commonly known to be caused by air pollution on the epidemiological scientific literatures. The study is a panel data over the period 2005-2016 across Swedish counties. I use information of annual concentrations of the air pollutants at a county level. I incorporated socio-economic control variables for estimating the health effect of air pollution and employed the fixed effect static estimation model.

It is observed that air pollution, specifically PM2.5 and TSP have a linear positive effect on the number of patients per 100K inhabitants in all the Swedish counties. Number of personnel per 100K inhabitants and population density are found to have positive and negative associations with the number of patients respectively. The results suggested a 1% increase in PM2.5 and TSP leads to a 0.113% and 0.177% increases in the number of patients per 100K inhabitants respectively. When breaking down all the selected disease, then SOx is positively associated with PHD, PM2.5 is positively associated with OFHD, GU and DU, and TSP is positively associated with PHD, OFHD, DAAC, OUDCS and DRS. The cost estimation indicated that the average annual per capita cost due to PM2.5 and TSP is SEK 18 558 and 18 594 respectively. The direct cost due to PM2.5 and TSP is around 0.11% of the Swedish GDP and indirect costs accounted for 0.10% of the Swedish GDP.

The overall results of this thesis suggest that it is time to initiate policies that will encourage a further reduction in the emissions of PM2.5 and TSP. It is also required that the awareness of people to air pollution to be elevated so that people would have to improve their avoidance behavior which in turn could lead to a better health outcomes.

Keywords: panel data, fixed effect model, health production function, SOx, PM2.5, TSP, patients per 100K inhabitants, direct costs and indirect costs.

Dedication

I dedicate this thesis work to my wife and my kids: Senait Sibhatu, Besaliel Tesfom and Debora Tesfom.

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Abbreviations

100K	100K
APHEA	Air Pollution and Health: A European Approach
CO	Carbon Monoxide
COPD	Chronic Obstructive Pulmonary Disease
CRHD	Chronic Rheumatic Heart Diseases
CVD	Cerebrovascular Disease
DAAC	Diseases of Arteries, Arterioles and Capillaries
DIPC	Disposable Income Per Capita
DRS	Diseases of the Respiratory System
DU	Duodenal Ulcer
FE	Fixed Effect
GU	Gastric Ulcer
HP	Health Care Personnel
IHD	Ischaemic Heart Disease
MCIC	Medical Cost per Individual per County
NBHW	National Board of Health and Welfare
NO2	Nitrogen Dioxide
OECD	Organisation for Economic Co-operation and Development
OFHD	Other Forms of Heart Diseases
OUDCS	Other and Unspecified Disorders of the Circulatory System
Patients100K	Number of Patients per 100K inhabitants
PHD	Pulmonary Heart Disease and Diseases of Pulmonary Circulation
PM10	Particulate Matter less than 10 $\mu g/m^3$
PM2.5	Particulate Matter less than 2.5 $\mu g/m^3$
Pop.	Population
PU	Peptic Ulcer
RGDP	Regional Gross Domestic Product per capita
SMHI	Swedish Meteorological and Hydrological Institute
SO2	sulphur dioxide
SOx	Sulphur Oxides
TSP	Total Suspended Particulate
WHO	World Health Organization

1 Introduction

The environmental hazards and damages due to ambient air pollution have been the main concern for many countries of the world. The global climate changes and its consequent effects on many parts of the world is an example of ambient air pollution effects. Thus, the adverse effects of air pollution on human health is a global concern. Does air pollution posit a threat to human health? Does ambient air pollution has any association with morbidity from diseases related to air pollution in Sweden? This thesis will try to answer through literature review and hypothesis testing, the above-mentioned fundamental questions and problems.

1.1 Problem background

The awareness of the adverse side effects of air pollution started as early as the thirteenth century where sea-coal burning was considered to have infected and corrupted the air and was associated to have a perilous effect on the people in England (Brimblecombe, 1999). Nevertheless, the nations of the world started to be more aware of the fact of air pollution and its effects starting with the Clean Air Act 1956 of the UK, the Montreal Protocol 1987, Kyoto Protocol 1997 and recently the Paris Agreement on Climate Change 2015.

In the past three decades, epidemiological studies around the globe demonstrated that there is an increasing trend of mortality and morbidity, which is attributable to increased air pollution levels (Krzyzanowski, 2002). Moreover, a cursory search on the environment, emissions, air pollution and human health literature displays a large number of search results. This indicates that environmental hazards and human health problems due to air pollution is a hot topic these days. OECD 2016 policy highlights show that ambient air pollution continues to be the largest global threat with multiple adverse effects on human health, agriculture and environmental impacts. It also projected the effects of air pollution to become much more severe in the coming years (OECD, 2016). According to the OECD policy highlights and WHO reports, air pollution will continue to impact at an alarming rate on the world economies and people’s quality of life (OECD, 2016; World Health Organization, 2016).

The statistical figures on the adverse effects of ambient air pollution are very alarming. The World Health Organisation estimates that globally 9 out of 10 people breathe polluted air and 7 million people die every year due to indoor and outdoor air pollution-related health problems (Osseiran & Lindmeier, 2018). This accounts for 12.5% of the total global death. It kills more people than malaria and AIDS combined and it could easily cross boundaries without any hindrance, and this dreadful phenomenon makes it global challenge and concern that demands a combined effort from the nations of the world (Piqueras & Vizenor, 2016)

According to the European Environmental Agency 2018 report, air pollution is one of the major causes of premature deaths and diseases in Europe (Guerreiro et al., 2018). For example, Chay and Greenstone (2003) on investigating the Clean Air Act of 1970 and its impact on infant mortality, they estimated that a 1% decline in total suspended particulates resulted in a 0,5% decline in the infant mortality rate (Chay and Greenstone, 2003). A study on air pollution on the current levels of the environmental air pollutants of the OECD countries indicates that the OECD countries have low levels of environmental air pollution by legislative and historical standards. However, even at these low levels, some recent studies from the United States demonstrated that infants in these countries are not risk-free from the adverse effects of air pollution (Janke *et al.*, 2009).

One of the 16 Swedish environmental objectives is ‘Clear Air’ and it clearly states that ‘the air must be clean enough not to represent a risk to human health or to animals, plants or cultural assets’ and it is the exposure to polluted air which could affect the human health negatively (Sverige and Naturvårdsverket, 2013). Therefore, it would be interesting to investigate the effects of air pollution on hospital morbidity in all the 21 Swedish counties, as it is part of the Swedish environmental objectives.

1.2 Problem statement

According to the World Health Organisation, the burden of disease due to air pollution is heaviest in low- and middle-income countries. Globally around 93% of all children and around 630 million below five years of age are exposed to air pollution (World Health Organization, 2018a). It is an alarming fact that the children of the world are highly exposed to the adverse effects of air pollution at their early ages. This asserts that the socio-economic impact of future generations is going to be very high if the situation continues in this scale.

Regional and national estimations show that around half million people die annually in Europe and around 7600 people die annually in Sweden due to air pollution-related diseases (Gustafsson et al., 2018; OECD and European Union, 2010). Reports to the European Environmental Agency shows that the continents’ air quality remains poor and 50-92% of the urban dwellers are exposed to particulate matter concentration above the World Health Organizations' Air Quality guidelines between 2000 and 2015 despite the actions taken to reduce particulate matter emissions and ambient concentrations in the region. There is also a risk of reduced lung function, respiratory infections, aggravated asthma and heart stroke disease that could result from exposure to ambient air pollution (World Health Organization, 2018b). In Europe air pollution is considered the second largest threat after climate change. However, based on the age-standardized mortality rate attributed to household and ambient air pollution (per 100K population) report of the World Health Organization, Sweden is one of the least affected countries in Europe (Guerreiro et al., 2018; World Health Organization, 2018). The burden of disease due to air pollution is heaviest in the low and middle-income countries, though to a lesser extent developed countries are not immune to the adverse effects of air pollution. The direct and adverse effects such as morbidity and mortality due to ambient air pollution are dramatic and devastating to human health and the environment. Therefore, it is quite reasonable to investigate the problem of air pollution in the Swedish context.

1.3 Aim and delimitations

For the purpose of devising and recommending optimal policy strategies to mitigate the adverse effects of ambient air pollution, a detailed and scientifically robust analysis is very important. In this regard, this thesis examines the following research hypothesis: Could exposure to ambient air pollution, in terms of the environmental air pollutants (sulphur oxides, particulate matter 2.5$\mu g/m^3$, particulate matter 10$\mu g/m^3$ and total suspended particulate) be associated to the morbidity rate in Sweden? Thus, my null and alternative hypotheses will be as follows:
H0: exposure to the environmental air pollutants have no effects on hospital morbidity.
H1: exposure to the environmental air pollutants have effects on hospital morbidity.

Generally, the objective of this study is to find out if there exists any association between the four environmental air pollutants and hospital morbidity of air-pollution-related diseases in the 21 Swedish counties. More specifically, this thesis will try to assess the following research objectives:

1. To estimate the effect of air pollution on morbidity in Sweden.
2. To estimate the direct and indirect costs of the health effects due to air pollution.

In this study, the focus is on ambient air pollution (outdoor air pollution) and its impact on hospital morbidity from diseases related to the four specified environmental air pollutants such as sulphur oxides, particulate matter 2.5μg/m^3 and particulate matter 10μg/m^3 and total suspended particulate. The study area includes all the 21 Swedish counties. Indoor and transboundary air pollutions and their effect on hospital morbidity are beyond the scope of this study. In addition, this study does not cover environmental damages due to air pollution.

1.4 Structure of the report

The remainder of this thesis is organized as follows. The second section examines the literature on air pollution and its effect on hospital morbidity. Section 3 presents the theoretical and empirical methodology, variable description, cost estimation models used in this thesis. Section 3 ends with methodological limitations. Results and discussions are presented in section 4. Conclusions and policy recommendations of this thesis are presented in section 5.

2 Literature review

This section reviews the scientific evidences and documentations related to ambient air pollution and its adverse impact on human health from global, regional and national perspectives.

Globally, some of the epidemical death due to ambient air pollution and its adverse effect on human health are shown below in figure 1 as estimated by the World Health Organization. It is also estimated that around 90% of the world population is being exposed to air pollution (World Health Organization, 2016). The figure shows that sizable proportion of all the deaths and diseases from lung cancer, acute lower respiratory infection, stroke, ischaemic heart disease and chronic obstructive pulmonary disease are caused by air pollution. We observe from figure 1 on a global scale that outdoor air pollution has the highest effect on chronic obstructive pulmonary disease followed by lung cancer, ischaemic heart disease, stroke and acute lower respiratory infections in children.

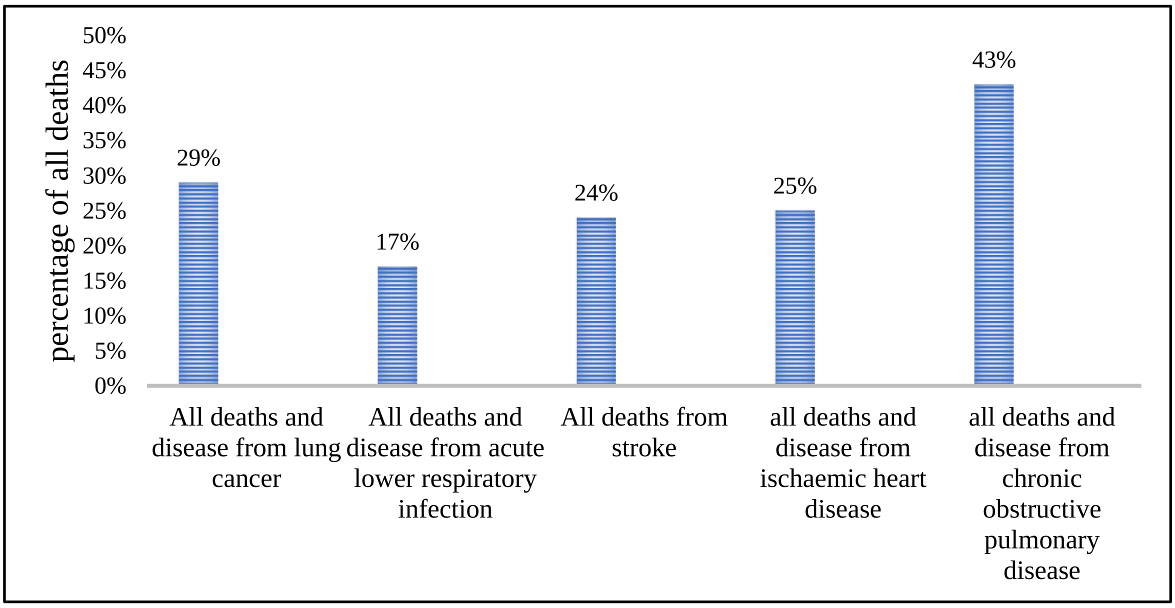

Figure 1. Worldwide Ambient Air Pollution: Effects and Exposure (source: Osseiran & Lindmeier (2018) and WHO report (2018) with some modifications)

Despite the efforts done by Sweden in reducing emissions the levels of particulate matter in the Swedish cities has relatively remained unchanged (Sjöberg, 2015). Gustafsson et al. (2018) using the URBAN model, health impact assessment and multivariate data analysis, estimates that in 2015 around 75% of the Swedish population was exposed to PM10 concentrations, where only 0.3% of the population exposed to concentrations above the standard environmental air quality (40 μg/m^3). Whereas, 80% of the Swedish population was exposed to PM2.5 in the same year, where 1% of the population was exposed above the environmental standard air quality concentrations (20 μg/m^3).

2.1 Health effects due to exposure to air pollution

Air pollution health studies determine the exposure extent based on the measurement at or near the individual's breathing zone where monitors of ambient air pollution are assigned to measure community exposures (O'Neill et al., 2003). The environmental health risk impact of air pollution is the process in which the ambient air pollution affects human health. It has three components: 1. *Contamination* - the measure of the degree of poisonous materials in a specified site and media. Contamination could come in several different forms, with thousands of toxic elements (in our case air pollutants) suspected to have adverse effects on human health. 2. *Exposure* - the quantification of human interaction with the pollutants. The existence of toxic compounds or pollutants in the environment is a problem to human health if there is a certain level of exposure of people to the pollutants. Therefore, degree of exposure, type of pollutants and the role of avoidance behavior by the individual will explicitly determine the health effects outcome. 3. *Dose-response* - the human exposure to the pollutants in the environment and it could be viewed a physiological health response due to air pollution conditional on the actual degree of human exposure to a given air pollutant (Graff Zivin and Neidell, 2013).

2.1.1 Health effects due to direct exposure to air pollution

Air pollution affects all people of all ages; it affects the poor and the rich alike. It affects all the nations of the world. Long-term exposure to air pollution increases the probability of a person to die early from heart disease, several types of respiratory diseases, lung cancer, cardiovascular diseases and other health problems, where mainly children and the elderly are being more vulnerable (Health Effects Institute, 2018; OECD and European Union, 2014). The Institute for Health Metrics and Evaluation estimates that diseases due to airborne pollutants accounted for around 67% of all life-years lost to environmentally related deaths and disabilities (Wendling et al., 2018). Lelieveld *et al.* (2015) estimated that the exposure to outdoor air pollution is a potential cause for 3.3 million deaths annually and it is projected to double by the year 2050 if nothing is done to mitigate the problem.

The OECD global projection from table 1 indicates that the effects of air pollution would more than double in 2060 in most of the cases. This is more devastating socially in terms of health effects and economically in terms of restricted labor productivity as a result of the adverse health effects from air pollution.

Table 1. Projected health impacts of air pollution at a global level

		2010	2060
Respiratory diseases (millions)	Bronchitis and asthma (children aged 5-19)	130	396
	Chronic bronchitis adults	4	10
Healthcare costs	Hospital admissions (in million)	4	11
Restricted activity days (million)	Low working days	1240	3750
	Restricted activity days	4930	14900
	Minor restricted activity days	630	2580

Source: OECD (2016)

A recent study by across the province of Ontario Canada using a cross-over design to evaluate the evaluate the association between emergency visits for respiratory diseases shows that a short-term increase in the levels of air pollution has been associated with upper and lower respiratory illnesses which resulted in emergency department visits (Szyszkowicz et al., 2018). Cohen et al (2017) used the integrated exposure-response function for a 25-year trend (1990-2015) to estimate the global, regional and country burden of disease attributable to ambient air pollution and they demonstrated that ambient PM2.5 is the fifth mortality risk factor in the year 2015. Exposure to PM2.5 has caused around 4.2 million global deaths in 2015 compared to around 3.5 million global deaths in 1990 and about 103.1 million disability-adjusted life-years in 2015. This is equivalent to 7.6% of total global deaths and 4.2% of global disability-adjusted life in 2015 and a 20% increase in deaths compared to 1990 (Cohen et al., 2017).

A study of Lanzhou, one of the most extreme air polluted cities in China, showed that there is a significant correlation between air pollutants and hospital admissions. Where a 10 $\mu g/m^3$ increases in PM10, SO2 and NO2 led to 0.2%, 0.5% and 1.1% increases of total respiratory diseases hospital admissions respectively while in other parts of China the respiratory disease related admissions were 0.4-1.6%, 1.3-3.0%, and 1.8-3.0% respectively (Tao et al., 2014). Kubatko & Kubatko, (2018) using linear health production function, studied economic estimations of air pollution health nexus, on 25 Ukrainian regions reveals that air pollution has a causal effect of 10.3%, 11%, 16% and 10.5-30% for cardiovascular disease, gastrointestinal morbidity, respiratory morbidity and lung cancer respectively.

According to Pope (2000), several studies have reported close associations between respiratory hospital admissions and particulate air pollution. Pope (2000) continues to report that studies, which investigated the emergency visits also, suggested an association between particulate air pollution and emergency visits for asthma, chronic obstructive pulmonary disease and related respiratory diseases. Pope (2000) also reports mortality and morbidity are common among the elderly, infants and individuals with chronic respiratory diseases. Anderson et al., (2003) asserts that the respiratory admission and relative risks associated with air pollutants do not vary with age, but there is an increasing trend for cardiovascular disease in the elderly who are 75 and above years old.

A study by Peel et al., (2005) on ambient air pollution and respiratory emergency department visits from year 2005 using Poisson generalized estimation equation, which involved a 4 million emergency department visits from Atlanta showed that upper respiratory infections (specific for infants and children) visits were positively associated with PM10, Ozone, NO2 and CO. PM2.5 and organic carbon were related to pneumonia (Peel et al., 2005). Ab Manan et al (2018) did an extensive review of 22 studies on air pollution and they noted that air pollution has an association with an excessive risk of 3.46 (95% CI, 1.67, 5.27) of total hospital admissions. PM2.5 and PM10 and SO2 have an increased effect on the cardiovascular and respiratory risk of hospitalization. They also noted that PM2.5 and PM10 have the highest risk of causing hospital admissions compared to the other pollutants. Both PM2.5 and PM10 were positively associated with hospital admissions from stroke or mortality from stroke, with a stronger association for PM2.5. The increase in relative risk was found to be 1.011 (95% confidence interval 1.011 to 1.012) per 10 $\mu g/m^3$ increase in PM2.5 concentration (Ab Manan et al., 2018; and Shah et al., 2015).

Nascimento et al. (2012) using a generalized linear model, carried an ecological study using hospital admissions data in São José dos Campos, São Paulo State, Brazil, with diagnosis of stroke, from January 1, 2007 to April 30, 2008 and they found out that stroke hospitalization were associated with exposure to PM10 with a relative risk of 12% due to an increased concentration of PM10. A study on fine particulate air pollution on 20 U.S cities suggested that PM10 have a positive effect on the death rate from cardiovascular and respiratory causes, where a $10\mu g/m^3$ increase in PM10 level of air pollution caused 0.68% increase of death (Samet et al., 2000). Newth & Gunasekera (2012) employed an agent-based modelling approach to capture the impact of the changes of particulate matter concentrations on mortality on the metropolitan city of Sydney. Their results suggested that a reduction in PM10 levels by half (relative to baseline levels) would lower mortality, respiratory hospital admissions and emergency visits.

A most recent study in five cities of Poland with a 20 million hospitalization using correlation analysis and distributed lag nonlinear models demonstrated that an increase in respiratory disease hospitalizations has been statistically significant and associated after peaks of particulate matter concentrations. Admissions have increased between 0.9 and 4.5% per 10 units of pollutant increase of PM2.5 and between 0.9 and 3.5% per 10 units of pollutant increase of PM10 (Slama et al., 2019). A study by Lagravinese, et al., (2014) in Italy using a linear model of hospital admissions function, found that higher levels of particulate matter were related with higher levels of hospital admissions for children. Whereas, the elderly's hospitalization was related to the higher levels of ozone. Nordling et al., (2008) in their investigation on traffic-related air pollution and childhood respiratory symptoms in four Swedish municipalities had demonstrated that an early in life exposure to moderate levels of emissions from traffic air pollution influences the development of different lung diseases and allergies in pre-school kids. A study in Stockholm shows that a reduction of exposure of 1 $\mu g/m^3$ per year of NO_2 for children aged 5-18 years were associated with a fewer asthma and hospital admissions cases and they were estimated to generate a benefit of 168 million SEK and 47000 SEK respectively (base year price 2000) (Nerhagen et al., 2013). The APHEA project of 1997 in western European cities found that an increase of $50 \mu g/m^3$ in SO2 caused a 3% increases in daily mortality and PM10 was associated with a 2% increase of daily mortality, while in Eastern European cities the consequence of $50 \mu g/m^3$ of SO2 brought about 0.8% daily mortality (Katsouyanni et al., 1997).

2.1.2 Health effects due to indirect exposure to air pollution

De Marco et al., (2019) suggests that air pollution has a considerable climate change effect which affects the forest ecosystem and water bodies through nitrogen deposition and tropospheric ozone and acidification of water bodies, which in turn, have negative human health effects. Thus, the environmental effects (which could have a health effects on the population) of air pollution includes damages to natural ecosystem disruptions , biodiversity, crop yield, forest yields, climate changes and limits to outdoor recreational activities and scenic areas (Guerreiro et al., 2018; New Zealand et al., 2018). For example, central and southern European grasslands exposed to high ground-level ozone and are at risk, which leads to plant community composition. Sulphur and nitrogen oxides potentially can pollute soils and freshwater through acidification effects, which may cause damages to the biodiversity of life on land and water bodies. It could also lead to eutrophication - the oversupply of nutrients in soil and water, which could have several damaging impacts on human health, land and water biodiversity (Guerreiro et al., 2018).

A study on climate variability and infectious diseases by Amuakwa-Mensah et al., (2017) in 21 Swedish counties using static and dynamic modelling frameworks of the health production function, suggested that parasitic and infectious disease patients in Sweden were affected by climate variability. An investigation of the impact of a congestion tax in central Stockholm suggested that policy-induced change in congestion pricing has reduced outdoor air pollution and the rate of acute asthma attacks among children below 5 years old (Simeonova et al, 2017). Kubatko & Kubatko (2018) employed the linear health production function to estimate the impact of air pollution on population health outcomes and they suggested that there is an increased cardiovascular diseases morbidity due to urbanization. Their result is in line with Malik et al. (2012), who studied global obesity: trends, risk factors and policy implications and found out that urbanization (which leads to increased air pollution) is one of the factors related to chronic non-communicable diseases. The study on Effects of urbanization on the incidence of non-communicable diseases by World Health Organization (2012) has also documented the evidence of urbanization as a health risk factor for non-communicable diseases such as pneumonia, cardiovascular diseases and heart disease. Akimoto (2003) notes that megacities as regional and global sources of air pollution and they posit serious health and social problems to the inhabitants. Karl & Trenberth (2003) suggested that human-induced activities have largely dominated our modern climate change, which is mainly the result of emissions, urbanization and land use changes.

2.2 Socio-economic effects of air pollution

The economic effects of air pollution range from market to non-market costs. The market costs include decreased productivity of labor, increased health expenditures (Guerreiro et al., 2018). According to the OECD policy highlights, non-market costs (linked with biophysical impacts, which may affect economic activity negatively) can be quantified using the premature death rates and the value of statistical life and the costs of pain and suffering from illness using willingness-to-pay estimates (OECD, 2016). The global costs due to ambient air pollution are estimated to be close to USD 3.2 trillion in 2015 and projected to increase to USD 18-25 trillion in 2060 (using constant 2010 USD). Where the OECD welfare costs from premature deaths were USD 1.4 trillion in 2015 and are expected to more than double (i.e. USD 3.4 – 3.5 trillion) by 2060 (OECD, 2016). It is also projected that these costs will reach about 2% of the European gross domestic product in 2060, which will lead to a decline in capital accumulation and economic slowdown (OECD, 2016). Claudio et al., (1999) on investigating the socioeconomic factors and asthma hospitalization rate in New York City noted people from low and median income groups had a high rate of hospital admissions. Evans et al., (1997) and Kelso et al., (1995) suggested that the level of education of patients could reduce the rate of hospital admissions. Table 2 below represents the different components of the socio-economic costs of the impact of air pollution. The market costs comprise of increased health expenses, decreased labor productivity and decreased agricultural productivities. The non-market costs represent disutility from illness and premature deaths. The environmental costs are decreased forest yield, climate changes, ecosystem disruptions, loss of biodiversity, limits to recreational activities and scenic areas.

Table 2. The broad cost categories due to air pollution

Air Pollution Costs	Market costs	Increased health expenses
		decreased labor productivity
		decreased agricultural productivity
	Non-market costs	disutility from illness
		premature death
	Environmental costs	decreased forest yield
		climate changes
		ecosystem disruptions and loss of biodiversity
		limits to recreational activities and scenic areas

Source: OECD (2016) with own modification

2.3 Contribution of this study

This research work deals with a critical health impact of air pollution in Sweden that potentially affects everyone. The research work simulates large quantities of data about air pollution and their association with morbidity (with 11 pollution-related diseases). This kind of analysis is not done much in earlier studies and thus can be utilized by concerned authorities for devising optimal policy decisions for mitigating the problem of air pollution, human health and environmental issues. The study is also in line with the 'Clear Air' Swedish environmental objective. Moreover, this thesis provides direct and indirect cost estimates associated with PM2.5 and TSP. This research study in one way or the other is related to 7 of the UN Sustainable Development Goals mainly: goals 3, 6, 7, 9, 11, 13, and 15[1].

[1] https://www.un.org/ga/search/view_doc.asp?symbol=A/RES/70/1&Lang=E accessed 20190607 at 15:54

3 Methodology

The conceptual and theoretical framework for this research follows the modelling of the health production function by Graff Zivin & Neidell (2013). Where the representative individuals' health production function is modelled as a function of the level of ambient air pollution, mitigation measures against pollution exposures and medical care expenses due to diseases from exposure to air pollution. In this study, I use the health production function to relate ambient air pollution to the morbidity rate in Sweden. Following Grossman's (1972) supposition of health as an investment good, and accompanied by Graff Zivin & Neidell (2013) extended health production model and the effects of health on productivity through the extensive margin - a process in which morbidity affects labour supply negatively hence influencing productivity through an intensive margin (Grossman, 1972). The intensive margin refers to the influence of productivity while holding labour supply constant. The intensive margin will enable the model to capture more accurately the effects of morbidity. In line with this, I will reformulate the health production function to investigate the impact of ambient air pollution on health. Thus, the health production function depends on air pollution (P), mitigation measures against the adverse effects of air pollution through avoidance behaviour (A) and medical care (Mc) as shown in equation (1):

$$H = h(P, A, Mc) \tag{1}$$

Where H is Health. Avoidance behaviour and medical care are expected to reduce the morbidity rate that comes from air pollution exposure. However, as pointed by Graff Zivin & Neidell (2013) these variables are different in their timing and costs. Where avoidance behaviour is an ex-ante action taken to prevent the effects of air pollution, whereas, medical care is an ex-post action to mitigate the effects due to air pollution exposure. Following Graff Zivin & Neidell (2013), I introduce a distinction between an individual's health (H) and illness incidences (ø). Thus, the representative individuals' health production function is given by:

$$H = h[Mc(ø), ø(\mathrm{P}, \mathrm{A})] \tag{2}$$

From equation (2), the illness incidences due to air pollution is a function of both air pollution and avoidance behaviour, in which, air pollution is expected to increase illness incidences while avoidance behaviour is expected to reduce illness incidences. The health of the representative individual is assumed to depend on medical care and illness incidences. Medical care is a function of illness incidences from air pollution, where the severity of illness increases medical care expenses. On the other hand, medical expenditure is assumed to reduce the severity of illness and disutility due to illness. Therefore, the individuals' health depends on both the medical expenditure and illness incidence. The individual's utility function depends on health, consumption (X) and leisure (L) and is given by:

$$U = u(H, X, L) \tag{3}$$

Assuming that the individual will allocate his/her total income (wage and non-wage) on consumption goods and mitigation measures. Thus, the individuals' budget constraint is written as:

$$\mathrm{I} + w(\mathrm{H})[\mathrm{T} - \mathrm{L}] = \mathrm{P_X X} + \mathrm{P_A A} + \mathrm{P_{MC} Mc} \tag{4}$$

Where 'I' represents the non-wage income, w(H) is wage income conditional on H, T is time, L is leisure, P_X is price of consumption goods, P_A is price of avoidance behaviour and P_{Mc} is price of medical care expenses. Solving the first order conditions from the maximization problem of the individual together with the budget constraint gives us:

$$\max_{X, L, A, M} \mathcal{L} = \mathrm{u(H, X, L)} + \lambda\, [I + w(H)[T - L] - \mathrm{P_X X} - \mathrm{P_A A} - \mathrm{P_{MC} Mc}] \tag{5}$$

The first order conditions are

$$\frac{\partial \mathcal{L}}{\partial X} = \frac{\partial \mathrm{u}}{\partial X} - \lambda \mathrm{Px} = 0 \tag{6}$$

$$\frac{\partial \mathcal{L}}{\partial L} = \frac{\partial \mathrm{u}}{\partial L} - \lambda w = 0 \tag{7}$$

$$\frac{\partial \mathcal{L}}{\partial A} = \frac{\partial \mathrm{u}}{\partial H}\left(\frac{\partial H}{\partial M}\frac{\partial M}{\partial \emptyset}\frac{\partial \emptyset}{\partial A} + \frac{\partial H}{\partial \emptyset}\frac{\partial \emptyset}{\partial A}\right)$$

$$-\lambda\left(\mathrm{P_A} + \frac{\partial w}{\partial H}\left[\frac{\partial H}{\partial M}\frac{\partial M}{\partial \emptyset}\frac{\partial \emptyset}{\partial A} + \frac{\partial H}{\partial \emptyset}\frac{\partial \emptyset}{\partial A}\right] * [\mathrm{T} - \mathrm{L}]\right) = 0 \tag{8}$$

$$\frac{\partial \mathcal{L}}{\partial M} = \frac{\partial \mathrm{u}}{\partial H}\frac{\partial H}{\partial M} - \lambda\left(\mathrm{P_{MC}} + \frac{\partial \mathrm{u}}{\partial H}\frac{\partial H}{\partial M}[\mathrm{T} - \mathrm{L}]\right) = 0 \tag{9}$$

Equations (6) and (7) represent the trade-offs between labor and leisure. From equations (8) and (9) it is possible to derive the following intuitive expression:

$$\frac{\left(\frac{dH}{dA}\right)}{\left(\frac{dH}{dM}\right)} = \frac{P_A}{P_{MC}} \tag{10}$$

Expression (10) argues that the marginal consumption of avoidance behavior and medical care for increasing the health of the individual will be equal to their price ratios.

Following Amuakwa-Mensah et al., (2017) and solving the first order conditions the optimal avoidance and medical treatment are obtained. These are functions of air pollution, the illness incidence (ø), the costs of avoidance behaviour ($\mathrm{P_A}$), medical measurements costs ($\mathrm{P_{Mc}}$), the costs of consumption goods ($\mathrm{P_X}$), medical cares ($\mathrm{P_{Mc}}$) and all other consumption goods ($\mathrm{P_X}$). Thus, optimal medical care and avoidance behavior functions are expressed as:

$$\mathrm{Mc} = f(\mathrm{P}, \text{ø}, \mathrm{P_{MC}}, \mathrm{P_A}, \mathrm{P_X}) \tag{11}$$

$$A = g(\mathrm{P}, \text{ø}, \mathrm{P_{MC}}, \mathrm{P_A}, \mathrm{P_X}) \tag{12}$$

We can observe from equation (11) and (12) that the medical treatment (which implicitly represents morbidity rate) and optimal avoidance behaviour are functions of all exogenous variables such as: air pollution, illness incidence, price of medical care, price of avoidance and price of consumption goods. Thus, medical care expense is a function of air pollution.

Therefore, it is possible to derive an expression for the relationship between air pollution and morbidity by finding the total derivative of equation (2):

$$\frac{dH}{dP} = \underbrace{\left(\frac{\partial H}{\partial Mc}\frac{\partial Mc}{\partial \emptyset} + \frac{\partial H}{\partial \emptyset}\right)}_{dH/d\emptyset} * \underbrace{\left(\frac{\partial \emptyset}{\partial P} + \frac{\partial \emptyset}{\partial A}\frac{\partial A}{\partial P}\right)}_{d\emptyset/dP} \tag{13}$$

The first argument in equation (13) is $(dH/d\emptyset)$ and the second argument is $(d\emptyset/dP)$. From Equation (13) it is clear that the reduced form effect of ambient air pollution on health status has two parts, which are the relationship between ambient air pollution and illness (that is, $(d\emptyset/dP)$.) and the degree to which illness is translated into health status (that is, $(dH/d\emptyset)$). The second expression of Equation (13) describes the net effect of ambient air pollution on illness incidence based on the individuals' level of exposure. The expression has two components: the first term is $(\partial\emptyset/\partial P)$, which represents the pure biological effect of ambient air pollution on illness incidences and the second term$((\partial\emptyset)/\partial A * \partial A/\partial P)$, which describes the ex-ante role of avoidance behavior to prevent illness incidences through mitigation measures against the adverse effects that may arise from exposure to ambient air pollution. If the avoidance behavior is significantly productive, it would be possible to observe no change on illness incidence due to ambient air pollution despite the existence of biological effect. However, if avoidance behavior is insignificant or insufficient, then the biological effect and the reduced form effects $(\partial\emptyset/\partial P)$, will be identical (Graff Zivin and Neidell, 2013).

Likewise, the first argument $(dH/d\emptyset)$ also has two components. The first expression $(\partial H/\partial Mc * \partial Mc/\partial\emptyset)$ and second expression$(\partial H/\partial\emptyset)$. Where the first expression represents the degree to which medical care measures, an ex-ante action reduces or eliminates the negative effects of ambient air pollution on health status. The second expression predicts the response of health to illness incidence, which reveals the degree to which induced illness incidences due to air pollution are not treated. If it is the case that the illness is untreatable or because of individuals negligence on seeking treatment for it (Graff Zivin and Neidell, 2013).

3.1 Empirical model and variable description

3.1.1 Estimation of the effects of air pollution

In this section, I present the empirical model and variable description. The estimation of the empirical model to investigate the effect of air pollution on morbidity is done by modifying the optimal medical care function in equation (11) by aggregating the number of patients per 100K inhabitants at the county level. In my empirical model, I include the vector of socio-economic and control variables. I consider how ambient air pollution coupled with socio-economic factors can explain the rate of morbidity in Sweden. The empirical model from equation (11) is given by:

$$M = f(P, D) \tag{14}$$

Where M represents the number of morbidity due to increases in ambient air pollution, P represents ambient air pollution variables and **D** represents a vector of socio-economic and control variables. Inclusion of socioeconomic factors is done for the purpose of external validity of the results. I estimate equation (14) under the assumptions of a static model where a current number of morbidity of patients do not depend on the previous number of morbidity of patients. To estimate the morbidity rate using the log-version of equation (14):

$$lnM_{it} = \beta_0 + \beta_1 lnP_{it} + \beta_2 lnDI_{it} + \beta_3 lnDI_{it}^2 + \delta ln\boldsymbol{D}_{it} + \eta_i + \gamma_t + \varepsilon_{\mathrm{it}} \tag{15}$$

M_{it} - represents the number of morbidity and is the dependent variable, which is expressed in terms of number of patients per 100K inhabitants. Each variable in equation (15) is a panel data set for county i in time period t. P is the pollution and is measured by ton/year. The terms DI (the disposable income per capita) and $\boldsymbol{D_{it}}$ represent the socio-economic and control variables, which includes education, number of healthcare personnel and population density, and η_i represents the county fixed effect and γ_t captures year fixed effect.

For the dependent variable, I consider the number of patients per 100K inhabitants. Morbidity in this study relates to patients per 100K inhabitants related to 11 diseases, which are classified to be related to air pollution. These diseases are chronic rheumatic heart diseases, ischaemic heart diseases, pulmonary heart disease and diseases of pulmonary circulation, other forms of heart disease, cerebrovascular diseases, diseases of arteries, arterioles and capillaries, other and unspecified disorders of the circulatory system, diseases of the respiratory system, gastric ulcer, duodenal ulcer and peptic ulcer. Data on patients per 100K inhabitants, diseases and health care personnel per 100K inhabitants is taken from the Swedish National Board of Health and Welfare database and all data on patients are based on in-patient care diagnoses (Socialstyrelsen, 2019). Data on education, population density, medical care per individual per county, regional GDP per capita and disposable income per capita are taken from Statistics Sweden database (SCB, 2019). Data on air pollution is taken from the Swedish Meteorological and Hydrological Institute database (SMHI, 2018).

I express the dependent variable as linear in ambient air pollution variables (i.e. sulphur oxides, particulate matter 2.5 and 10 and total suspended particles). Educational level, population density per square kilometer and total number of health personnel per 100K inhabitants enter in the model linearly and disposable income per capita enters in a non-linear form. I introduce dummy trend and this variable will capture the sudden decline of patients per 100K inhabitants after the year 2012. Finally, I am taking the natural log of all the variables and thus, the coefficients of my regression analysis represent the elasticities of the respective variables.

3.1.2 Cost estimation of the effects of air pollution

In estimating the cost of the effects of air pollution on the patients per 100K inhabitants, I follow the works of Kubatko & Kubatko (2018), Ostro (1994). I first estimate β_1 from equation (15) and then multiply it by the average change of pollution of the specified air pollutants. This gives us the marginal health effect of the specified air pollutant as:

$$dlnM_i = \beta_1 * dlnP_i \tag{16}$$

Where $dlnM_i$ – change in morbidity in county $i;$ β_1- the marginal effects of air pollution (the estimated slope coefficient of the pollution in equation (15)) in county i *and* $dlnP_i$ – the change in pollution levels in each county. For the purpose of cost estimations $dlnM_i$ will be expressed in level form as follows:

$$M_i = e^{dlnM_i} \tag{17}$$

M_i- Morbidities due to air pollution. However, the estimation of the direct costs attributed to air pollution is more complicated due to data unavailability of the disease specific cost. Thus, following Kubatko & Kubatko, (2018), I utilize the available data on the average hospitalization costs per capita as proxy measures for the cost of the air pollution related diseases. The direct cost will capture the health expenditures due to air pollution related morbidities. The total direct medical costs per capita per county (DMC_i) due to air pollution will then be computed as:

$$DMC_i = PC_i * M_i \tag{18}$$

Where PC_i – is the general average annual medical cost per capita per county.

Again following Kubatko & Kubatko, (2018), the indirect costs (opportunity cost) is calculated by multiplying the air pollution caused morbidities by the county gross domestic product per capita. Indirect costs will capture the low working days, restricted activity days, minor restricted activity days, lost labor productivities and other loses due to air pollution caused morbidities.

$$IC_i = RGDP_i * M_i \tag{19}$$

Where, IC_i – the indirect costs and $RGDP_i$ – the county gross domestic product per capita. Then the total economic cost due to air pollution related morbidities will be the sum of the DMC_i *and* IC_i from equations (18) and (19).

Variable description

Table 3 presents the list of the variables of interest: dependent variables

Table 3. Dependent and explanatory variables

Dependent variables	**Explanatory variables**	**Socio-economic control variables**
Total number of patients per 100K inhabitants	Sulphur oxides	Disposable income per capita per county
	Particulate matter 2.5 μg/m^3	Educational level
	Particulate matter 10 μg/m^3	Population density per square kilometre
	Total suspended particles	Total number of health personnel per 100K inhabitants

This research will rely on a panel data fixed effects model. I will use a panel data of ambient air pollution and morbidity for the 21 Swedish counties from 2005 to 2016. I use a static county fixed effect model.

3.2 Methodological limitations

The present study is not without limitations. I rely on the online data of air pollution available from SMHI database, where data is collected from four monitoring sites and thus, as pointed out by Gustafsson et al., (2018) it will be impossible to fully capture the distribution of air pollutants throughout Sweden. This research also relies on the online data of the number of patients provided by the National Board of Health and Welfare in Sweden. Therefore, there could be cases where the diseases might happen to be less serious and be remedied without going to hospital. In such cases, the analysis in this research could not capture such incidences. The research also depends on online data on medical cost per individual per county, in such case the cost is not specific for the air pollution-related diseases but is an average value for all diseases. If a county has many elderly who will have health problems anyway or accept many immigrants who might come to Sweden with related diseases, such cases would overestimate the cost per capita of that county compared to other counties with less number of elderly. Thus, if one could get access to the cost per individual per specific disease related to air pollution, the results could be much different.

In my analysis, I did not control for the speed of wind, which could have an impact on the air pollution weights in respective counties. The logarithmic empirical model used in this research, implicitly assumes that the proportion of air pollution in a county is proportional to the population in the county (Haeger-Eugensson et al., 2003). This assumption would not hold if one could obtain data on height and speed of wind in respective counties. As pointed out by Anderson et al., (2003) a time series data on air pollution might not provide direct information about the degree of patients and such data might be short of estimating more accurately the effects of air pollution on morbidity. Therefore, the results might change if one could use cohort studies instead of annual panel data. Those selected diseases, which are known to be caused by air pollution, could also be caused by some other factors (example: pollen during summer) that might not be shown up in my results.

There is no direct control on avoidance behaviour in my models. Neidell (2004) for example states that household responds with avoidance behaviour when provided information concerning air pollution and suggests it should be accounted for when measuring the effect of air pollution on health. As pointed out by Li et al., (2018) to capture the individual effect of the air pollutants, one would need to have more information on other confounding factors, like smoking, exposure to other pollutants, lifestyle risk factors, chronic diseases burden, physical activities and pre-existing diseases. In the Swedish context, one also needs to have control of the number of immigrants with related diseases.

4 Results and discussion

4.1 Descriptive statistics and correlation matrices

Table 4 describes the summary statistics of the variables of interest like number of observations in my data, mean, standard deviation, minimum and maximum amounts of the specified variables. Among the air pollutants, TSP has the highest record of ton/year followed by PM10, SOx and PM2.5. Here the values of the variables are expressed in natural logarithmic form. All the variables are in natural log form to deal with outliers and all computation is done with Stata 15 software program unless otherwise indicated.

Table 4. Descriptive statistics of dependent and independent variables

Variables	Obs	Mean	Std.Dev.	Min	Max
lnTotal patients 100K	252	8.55	0.11	8.20	8.76
lnSOx	252	7.017	1.027	4.47	8.699
lnPM2.5	252	6.904	0.578	5.983	8.381
lnPM10	252	7.429	0.541	6.695	8.877
lnTSP	252	7.679	0.566	6.793	9.392
lnDIPC	252	5.126	0.135	4.836	5.472
lnTotal Edu.	252	12.326	0.792	10.642	14.328
lnPop. density	252	3.211	1.147	.916	5.852
lnTotal HP 100Ks	252	7.541	0.11	7.301	7.846
lnMCIC	252	9.81	0.118	9.555	10.025
lnRGDP	252	12.712	0.153	12.417	13.344

Figure 2 presents the total number of patients per 100K inhabitants in Sweden over the years 2005-2016. It shows that there was a slight decline in the number of patients per 100K inhabitants in the first three years (2005-2007) and it was almost constant from 2008 to 2012. Then the number of patients per 100K inhabitants in Sweden has shown a radical decline up until 2016.

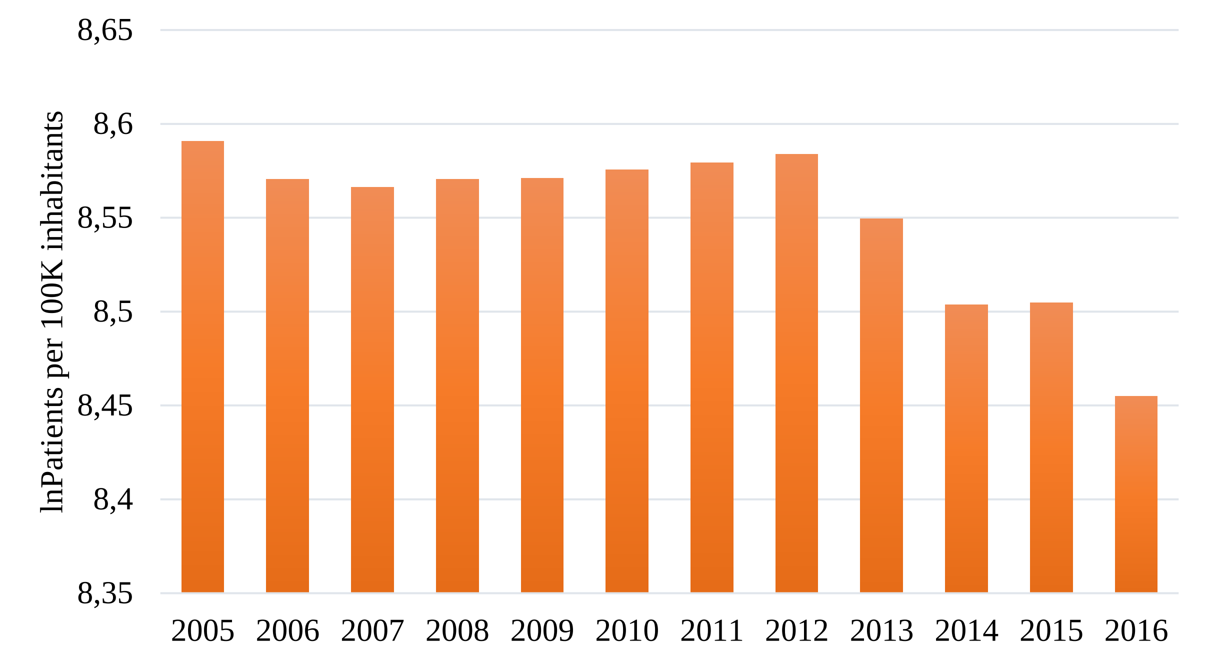

Figure 2. The total number of patients per 100K inhabitants in Sweden over the years.

Figure 3 displays the distribution of the number of patients across the Swedish counties over the years (2005-2016). From the figure, we observe that Kalmar county has the highest number of patients per 100K inhabitants followed by Norrbotten, Dalarna, Gotland, Gävleborg and Västernorrlan counties. Whereas, Stockholm county has the least number of patients per 100K inhabitants followed by Uppsala, Östergötland and Örebro counties.

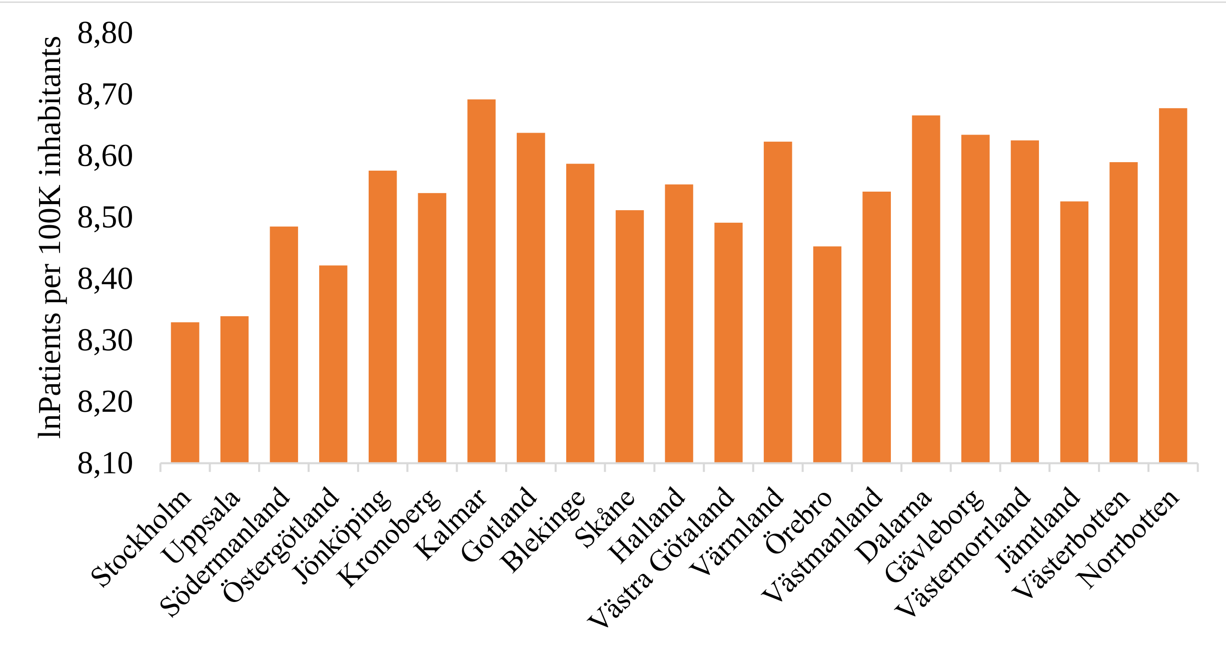

Figure 3. Distribution of the number of patients across the Swedish counties (2005-2016). Source: National Board of Health and Welfare database, Sweden

Figure 4 presents the average amount (ton/year) of the air pollutants for all the Swedish counties over the years (2005-2016). It shows that Stockholm has the highest record of air pollution in terms of TSP, PM10 followed by Västra Götaland, Norrbotten and Skåne. It is also observed that Västerbotten has a high record of air pollution in terms of SOx followed by Västra Götland, Skåne, Stockholm and Norrbotten. It is interesting to see that Kalmar has the highest record of the number of patients per 100K inhabitants (see figure 3), though it is not in the list of the highly polluted counties. Stockholm and Västra Götaland on the other hand, are among the counties with the least number of patients per 100K inhabitants (figure 3) despite the fact that they are among the highest air polluted counties. Since I have an annual data, it could be the case that there are other factors, which are not captured by the model. For example, if one could get a seasonal data on patients, which will capture the summer (for example: with lots of pollen causing respiratory diseases) and winter seasonal difference, this might give different results from what we have now. One would expect the counties with the largest Swedish cities to show a high record of air pollution. This is true for Stockholm and Västra Götaland counties, but this is not the case for the other three counties with big cities - Uppsala, Skåne and Västmanland counties. However, Norrbotten does not have many large cities, but it has large mining activities, which could be the cause for high particulate matter air pollution.

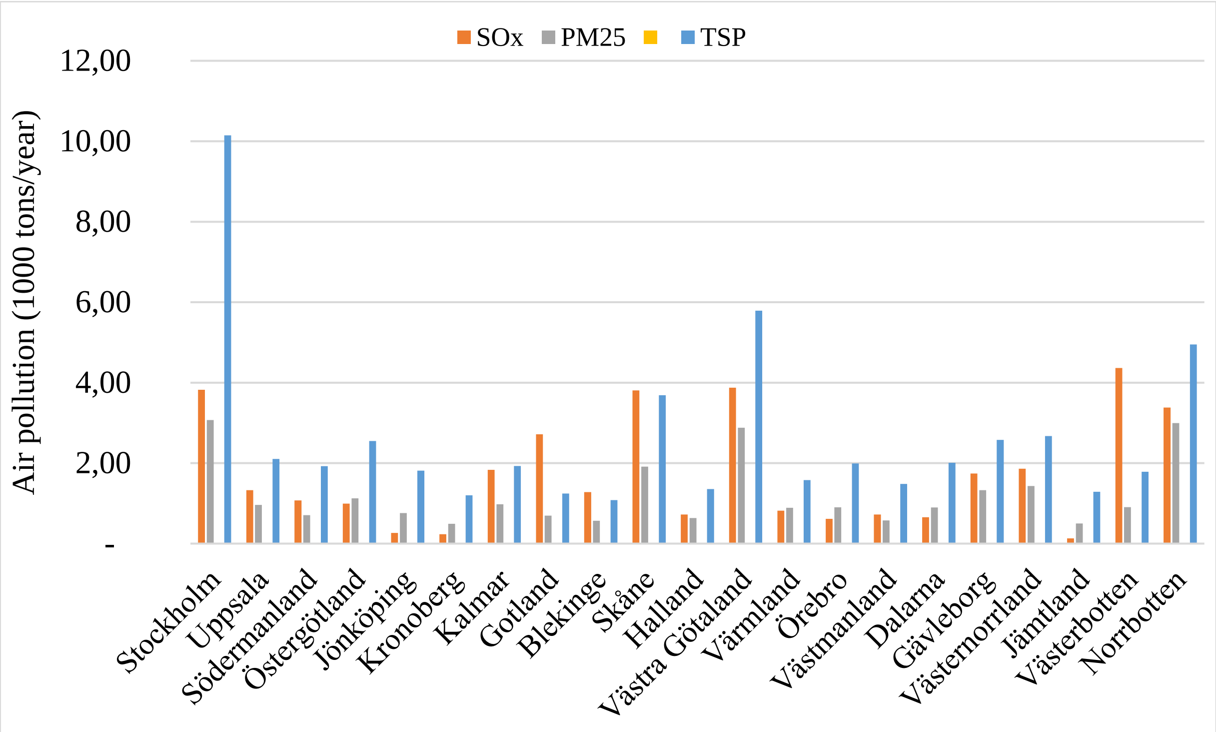

Figure 4. The average amount (ton/year) of air pollutants across the Swedish counties (2005-2016)

Figure 5 displays the levels of air pollution (SOx, PM2.5 and TSP) in 1000 ton/year over the years. TSP records the highest followed by SOx and PM2.5 over the years. The figure presents SOx and PM2.5 as exhibiting a declining trend throughout the years. TSP shows small fluctuations but overall it exhibits a small increasing trend over the years.

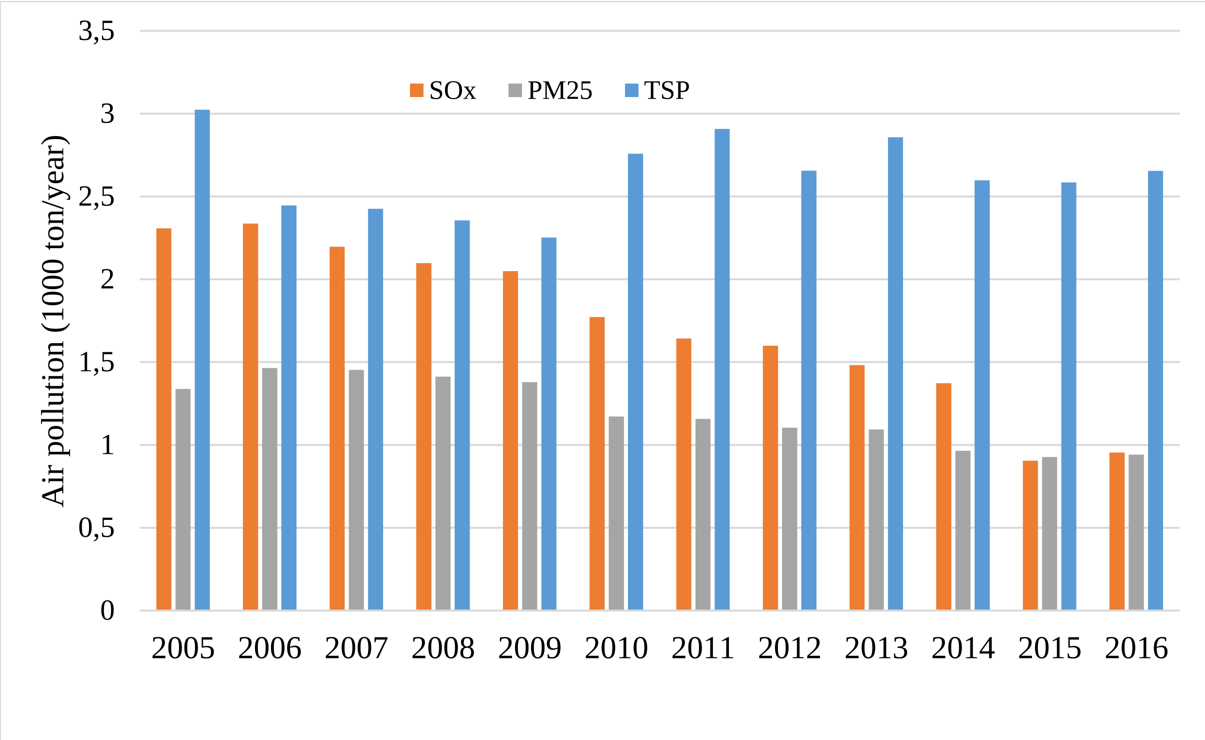

Figure 5 Air pollution levels in Sweden over the years 2005-2016

4.2 Air pollution and the number of patients

Table 5 presents the regression results of the dependent variable total number of patients per 100K inhabitants due to air pollution. I used the year fixed effect (as dummy trend) to capture the drastic decline in the number of patients from the year 2012 onwards as depicted in figure 2 above. The sudden drastic changes in the number of patients might be explained by the strategic Swedish climate change policies undertaken in the years before 2012. For example, the Swedish Institute claims that Sweden has 52% of renewable source of energy in 2014. Sweden more than any other country's per capita had allocated SEK 4 billion as a green climate fund for the UN. Sweden is one of the leading countries in the case of sustainability through its innovative sustainable solutions investment where expenditure on research and development in Sweden comprises 3.3% of GDP in 2013. In 2012, Sweden had a very high environmentally related tax revenue 2.52% of its GDP compared to other OECD average of 1.54. This could have encouraged many firms and companies to switch from fossil fuels to biofuels through the years and thus reducing emissions of air pollutants (Swedish Institute, 2018). Moreover, Sweden has registered a 22% reduction in GHG emissions in 2013 compared to 1990 (Swedish Institute, 2018). In addition, the sudden decline could also be attributed to the revised Gothenburg Protocol 2012, which aims at reducing SO2, NOx, PM2.5 and other emissions with main focus on improvements for human health and ecosystems protection expecting committed emissions reduction in 2020 (Amann et al., 2012). The mentioned developments in Sweden might indirectly explain the significant negative association of year fixed effect with the number of patients. It is natural to expect that the National Board of Health and Welfare might have devised some kind of policies to reduce the number of patients over the years, but such policies that have direct effects through the Swedish health care authorities could not be identified during the course of this thesis. In any case, the negative year fixed effect results of this thesis is comparable to the results of Lagravinese et al., (2014) from Italy.

In table 5, the air pollutants are taken one at a time and finally, all pollutants are taken together. The results show that SOx, PM2.5 and PM10 are not statistically significant when taken separately, whereas TSP is significant at 5% level. It suggests that a 1% increase in TSP would result in a 0.06% increases in the number of total patients per 100K inhabitants (see column 4 of table 5). This result is comparable with the results of Samet et al., (2000) who investigated particulate air pollution on 20 U.S cities which suggested that 10µg/m^3 increase PM10 (which was taken as part of the suspended particulate in their study) caused a 0.68% increase in mortality. It is also in line with the results of Lagravinese et al., (2014) in Italy, where they found that higher levels of particulate matter were related to higher levels of hospital admissions for children.

However, when all the pollutants were taken together the results indicate that PM2.5, PM10 and TSP are significant. PM2.5 and TSP have a positive association with the total number of patients per 100K inhabitants at 5% level of significance. Thus, a 1% increase in PM2.5 and TSP leads to a 0.113% and 0.177% increases in the number of patients respectively. The effects of PM2.5 in this research could be compared with the Polish results on PM2.5, a recent study undertaken by Slama et al., (2019) with 20 million hospitalization cases were investigated and found that 10 units increase in PM2.5 increased hospital admission by 0.9%. Peel et al., (2005) investigation in Atlanta, which involved 4 million emergency visits, suggested a positive association between upper respiratory infections and PM2.5. Ab Manan et al., (2018) also found out a positive association between PM2.5 and hospital admission where a 10µg/m^3 increase in PM2.5 caused a 1.01 relative risk of hospital admissions. The results of this thesis also reaffirm the positive association of particulate matter with ischaemic heart disease and cerebrovascular disease in Sweden by Toren et al., (2007). The smaller percentage changes in patients attributed to the air pollutants in Sweden could be because Sweden has a more or less constant emissions over the years as shown in figure 5 above.

Table 5 Number of patients per 100K inhabitants due to air pollution

VARIABLES	(1) lnTotal Patients 100K	(2) lnTotal Patients 100K	(3) lnTotal Patients 100K	(4) lnTotal Patients 100K	(5) lnTotal Patients 100K
lnSOx	-0.006				-0.008
	(0.015)				(0.012)
lnPM2.5		0.032			0.113**
		(0.035)			(0.052)
LnPM10			0.058		-0.215*
			(0.041)		(0.113)
lnTSP				0.060**	0.177**
				(0.028)	(0.064)
lnDIPC	-0.422	-1.697	-0.993	0.064	-0.290
	(3.497)	(3.607)	(3.157)	(3.384)	(4.166)
$lnDIPC^2$	0.024	0.155	0.086	-0.020	0.019
	(0.347)	(0.361)	(0.315)	(0.336)	(0.416)
lnTotal edu.	0.059	-0.013	-0.056	-0.035	-0.038
	(0.252)	(0.286)	(0.289)	(0.281)	(0.300)
lnTotal HP100K	0.613**	0.604**	0.602**	0.591*	0.496*
	(0.272)	(0.235)	(0.265)	(0.288)	(0.260)
lnPop. density	-0.477**	-0.508***	-0.529**	-0.526**	-0.539**
	(0.175)	(0.171)	(0.203)	(0.210)	(0.191)
Dummy trend	-0.065***	-0.064***	-0.064***	-0.064***	-0.061***
	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)
Constant	6.317	10.203	8.804	5.965	7.541
	(10.476)	(11.612)	(10.463)	(10.803)	(13.007)
Observations	252	252	252	252	252
R-squared	0.565	0.568	0.572	0.581	0.597
Number of id	21	21	21	21	21
County FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES

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

From table (5) we observe that total health personnel per 100K inhabitants is positively associated while the population density is negatively associated with the number of patients per 100K inhabitants at different levels of significance. It might be the case that the more the number of health personnel a county has the more the number of patients it can serve in a given time and place. However, this result is in contrast to the results found by Amuakwa-Mensah et al., (2017), where they found that number of health personnel had a negative and significant association with infectious diseases in the 21 Swedish counties. Lagravinese et al., (2014) results though not significant but suggests a negative association between population density and COPD hospital admissions. The negative association of population density with the number of patients could be interpreted as the number of people increase the per capita share of the air pollutants would be thinly distributed among the large population size, thus leading to a fewer people being sick. Separate results without dummy trend are available at appendix table 11.

4.2.1 Air pollution and the number of patients by age group

Table 6 represents the results of total number of patients per 100K inhabitants according to three age groups. The children (0 to 14 years old), the middle ages or working group (15-64 years old) and the elderly (65 and above years old). It is worth to mention first that population density has a negative and significant association for all age groups except children. Year fixed effect continues to have a significant and negative association for all age groups.

Group 1. Children ages 0 – 14 years: The children aged 0 to 14 years are presented as not being affected by the four air pollutants (column 1 of table 6), which is not the case in most literature. However, a further age breakdown (see appendix table 12 and 13) shows that the selected air pollutants have no association with infants 0-4 years old. When it comes to children from 5-9 years old, SOx and PM2.5 have shown a positive association. Where 1 % increase in SOx and PM2.5 is associated with 0.124% and 0.875% increase in the number of patients per 100K inhabitants at 10% and 5% respectively. Compared to SOx, PM2.5 has the highest impact on children patients 5-9 years old (appendix, column 2 of table 12). Children between 10-14 years old are affected only by PM2.5 (see appendix column 3 of table 12). The results of Nordling et al., (2008), where they found that air pollution exposures of infants under 4 years old was associated with an excess risk of persistent wheezing whereas my results show that infants below 4 years old are not affected by any of the air pollutants. An epidemiological study on the effects of air pollution on the health of children by Buka et al., (2006) also suggested that air pollution is positively associated with morbidity, mortality, school absenteeism and altered immunity adverse respiratory health outcomes. The results of this research matches weakly with the results of Neidell (2004) who used a linear health production model to estimate the effects of air pollution on childhood asthma in California, found a substantial impact of air pollution on infants compared to older children. Nevertheless, still older children (5-14 years old) are positively associated with SOx and PM2.5 which is similar to the results obtained by Neidell (2004). On the other hand, PM10 was not significant for this age group. This is also suggested by the results of Neidell (2004) and Lagravinese et al., (2014) for the same age group of 0-14 years.

Table 6. Number of patients per 100K inhabitants by age group

VARIABLES	(1) lnPatients100K 0 -14YRS	(2) lnPatients100K 15-64YRS	(3) lnPatients100K ≥ 65 YRS
lnSOx	0.033	0.010	-0.005
	(0.052)	(0.021)	(0.014)
lnPM2.5	0.269	0.198***	0.056
	(0.191)	(0.058)	(0.045)
lnPM10	-0.435	-0.288**	-0.126
	(0.443)	(0.115)	(0.084)
lnTSP	0.186	0.259***	0.152***
	(0.224)	(0.066)	(0.053)
lnDIPC	-4.406	2.023	-0.303
	(10.169)	(4.726)	(3.755)
lnDIPC^2	0.388	-0.224	0.009
	(1.034)	(0.473)	(0.373)
lnTotal edu.	0.904	0.208	0.155
	(1.060)	(0.321)	(0.217)
lnTotal HP 100K	0.557	0.726**	0.217
	(0.893)	(0.267)	(0.234)
lnPop. density	-0.634	-0.514**	-0.474***
	(0.532)	(0.229)	(0.115)
Dummy trend	-0.095**	-0.069***	-0.054***
	(0.036)	(0.018)	(0.011)
Constant	7.364	-2.278	10.336
	(38.772)	(14.212)	(10.353)
Observations	252	252	252
R-squared	0.460	0.679	0.680
Number of id	21	21	21
County FE	YES	YES	YES
Year FE	YES	YES	YES
Controls	YES	YES	YES

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

Group 2. Working group aged 15-64 years: The number of total patients in the age group 15-64 years old has a positive association (at 1% level of significance) with PM2.5 and TSP (see column 2 of table 6). The results in table 6 column 2 suggest that a 1% increases in PM2.5 and TSP leads to an increased number of patients per 100K inhabitants by 0.198% and 0.259% respectively for the age group 15-64 years old in Sweden which is closely comparable to Li et al., (2018) results. Li et al., (2018) also found out that 79% of ≥ 65 years old are under the adverse effects of PM2.5, whereas the result of this thesis shows that 15 to 64 years old are positively associated with PM2.5. The results of this research are also comparable to the results of Ab Manan et al., (2018) , Li et al., (2018) Nordling et al., (2008), Peel et al., (2005), Shah et al., (2015), Slama et al., 2019 and many others in the literature. For example, Li et al., (2018) using time-series design with generalized additive Poisson model to assess the effect of PM2.5 on heart disease hospitalization found that a 10 $\mu g/m^3$ increases in PM2.5 concentration brought a 0.35% increase in heart disease hospitalization in Beijing, China.

A further age breakdown can be seen from the appendix table 12 and 13. The results of table 12 and 13 in the appendix suggest that age groups 15-19, 20-39, 55-64 years old are all positively associated with PM2.5and TSP at different levels of significance. SOx has a positive and significant association with adults 40-44 years old. Moreover, TSP is positively associated with 50-54 years old patients.

Group 3. The elderly aged 65 and above years: TSP (at 1% level of significance) has a positive and significant association with the elderly's number of patients per 100K inhabitants (table 6 column 3). A 1% increase in TSP brings 0.152% increase in the number of patients per 100K inhabitants. It is interesting to see that similar results were observed by Vigotti et al., (1996) where TSP was positively associated (1.05 relative risk) with the mortality rate of the elderly aged 65 and above. It also goes along with the results obtained by Ding et al.,(2017), Hüls et al., (2019), Ohlwein et al., (2016), Schnass et al., (2018), and Yang et al., (2018) where all found a positive association between ambient air pollution and people of 55 and above years old. More specifically Anderson et al., (2003) study undertaken in London and Tao et al., (2014) study in China both found that the daily hospital admissions for the respiratory disease were positively associated with the elderly 65 and 75 and above years old respectively. The results of Cournane et al.,(2016) in Ireland with 82 421 hospital admission episodes found that the patients with respiratory admissions due to particulate matter air pollution were on average 68.4 years old.

A further age breakdown can be seen from appendix table 12 and 13, where 70-79 years old patients are all positively associated with PM2.5 and TSP at different levels of significance. In addition, TSP is positively associated with 65-69 and 80+ years old patients.

4.3 Air pollution and health effects

Table 7 represents a case study of the effect of air pollution on the number of patients for respiratory diseases. The four air pollutants are taken one at a time to see if they have any association with the diseases of respiratory systems. The regression results show that SOx has a significant and negative association with the respiratory diseases at 5% level of significance (column 1 of table 7). However, a negative association of SOx is not widely available in the literature. The other two air pollutants mainly PM2.5 and PM10 did not show any significant relationship with the respiratory diseases (columns 2 and 3 of table 7). However, TSP was found to be significantly associated with the diseases of respiratory systems at 5% level of significance (column 4 of table 7). Where a 1% increase in TSP would result in 0.114% increase in respiratory diseases.

Table 7 Patients of diseases of the respiratory system per 100 thousand inhabitants

VARIABLES	(1) lnTotal Patients 100K	(2) lnTotal Patients 100K	(3) lnTotal Patients 100K	(4) lnTotal Patients 100K	(5) lnTotal Patients 100K
lnSOx	-0.040**				-0.038**
	(0.019)				(0.017)
lnPM2.5		-0.024			0.071
		(0.052)			(0.085)
lnPM10			0.083		-0.236
			(0.085)		(0.217)
lnTSP				0.114**	0.247**
				(0.049)	(0.107)
lnDIPC	0.899	-0.721	-1.758	0.147	3.056
	(3.827)	(4.265)	(3.667)	(3.791)	(4.687)
lnDIPC^2	-0.082	0.078	0.191	0.002	-0.291
	(0.383)	(0.433)	(0.371)	(0.376)	(0.472)
lnTotal edu.	0.289	0.308	0.100	0.087	0.213
	(0.356)	(0.436)	(0.485)	(0.427)	(0.478)
lnTotal HP100K	0.444	0.593	0.530	0.494	0.339
	(0.352)	(0.374)	(0.354)	(0.390)	(0.374)
lnPop. density	-0.211	-0.182	-0.281	-0.299	-0.269
	(0.287)	(0.335)	(0.375)	(0.351)	(0.354)
Dummy trend	-0.062***	-0.061***	-0.060***	-0.058***	-0.057***
	(0.012)	(0.013)	(0.013)	(0.014)	(0.015)
Constant	-1.664	0.879	5.785	1.225	-5.937
	(12.904)	(15.656)	(13.987)	(12.829)	(16.030)
Observations					
R-squared	252	252	252	252	252
Number of id	0.175	0.161	0.170	0.201	0.229
County FE	21	21	21	21	21
Year FE	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES

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

When all the air pollutants were regressed together against the disease of respiratory system, TSP continues to show a significant positive association with a higher effect. Where a 1% increase in TSP now brings about 0.247% increase in respiratory diseases. The consistent positive association of particulate matter with respiratory diseases has been demonstrated by several studies in the epidemiological and environmental economics scientific literature. Cournane et al.,(2016) investigated 44 660 patients admitted in Ireland and found that 39.5% of the patients admission was a respiratory disease due to air pollution. Vigott et al., (1996) on their study on the short-term effects of urban air pollution on respiratory health in Milan, Italy, found that a 100µg/m^3 increase in TSP caused a 4% increase in respiratory diseases hospital admissions.

4.4 Air pollution and all disease breakdown

Table 8 presents, in brief, the association of the significant air pollutants with different air pollution-related diseases in Sweden. In total there are seven reported diseases, which have a significant association with air pollution in Sweden such as: pulmonary heart disease and diseases of pulmonary circulation, other forms of heart disease, diseases of arteries, arterioles and capillaries, other and unspecified disorders of the circulatory system, diseases of the respiratory system, gastric ulcer and duodenal ulcer. Table 8 also shows that TSP is the most adverse air pollutant affecting 5 diseases related to air pollution, followed by PM2.5 that affets 3 diseases and SOx is the least adverse air pollutants as per the results. For further detailed information on the air pollutants effects on the selected disease is available at appendix table 14 and 15.

Table 8. Association between air pollutants and diseases

	SOx	PM2.5	TSP
PHD	√		√
OFHD		√	√
DAAC			√
OUDCS			√
DRS			√
GU		√	
DU		√	

4.5 Cost estimations of health effects due to air pollution

Table 9 presents the statistical summary of the cost estimations attributed to air pollution from PM2.5 and TSP. In table 9 we see that the average annual per capita cost over the years 2005-2016 is estimated around SEK 18 558 due to PM2.5 and around SEK 18 594 due to TSP.

Table 9 Descriptive Statistics annual per capita cost due to air pollution

Variable	Obs	Mean	Std.Dev.	Min	Max
PM2.5	231	18557.62	1964.507	14293.71	23070.16
TSP	231	18593.71	2076.696	13584.96	23062.54

Figure 6 presents the average per capita cost per county attributed to PM2.5 and TSP air pollution over the years 2005-2016. In figure 6, we observe that within the counties the average per capita cost attributed to both the air pollutants are more or less equal. Among the Swedish counties, Norrbotten has the highest per capita cost followed by Kalmar and Västernorrland. Gävleborg, Södermanland, Värmland, Örebro, Västmanland, Dalarna, Gotland Västerbotten and Jämtland exhibit more or less similar average of per capita cost. Stockholm and Skåne are the counties with high levels of pollution but their average per capita cost due to air pollution is not very high (see figures 4 and 6). On the other hand, Kalmar with least air pollution record has a high average per capita cost due to air pollution (see figure 4 and 6).

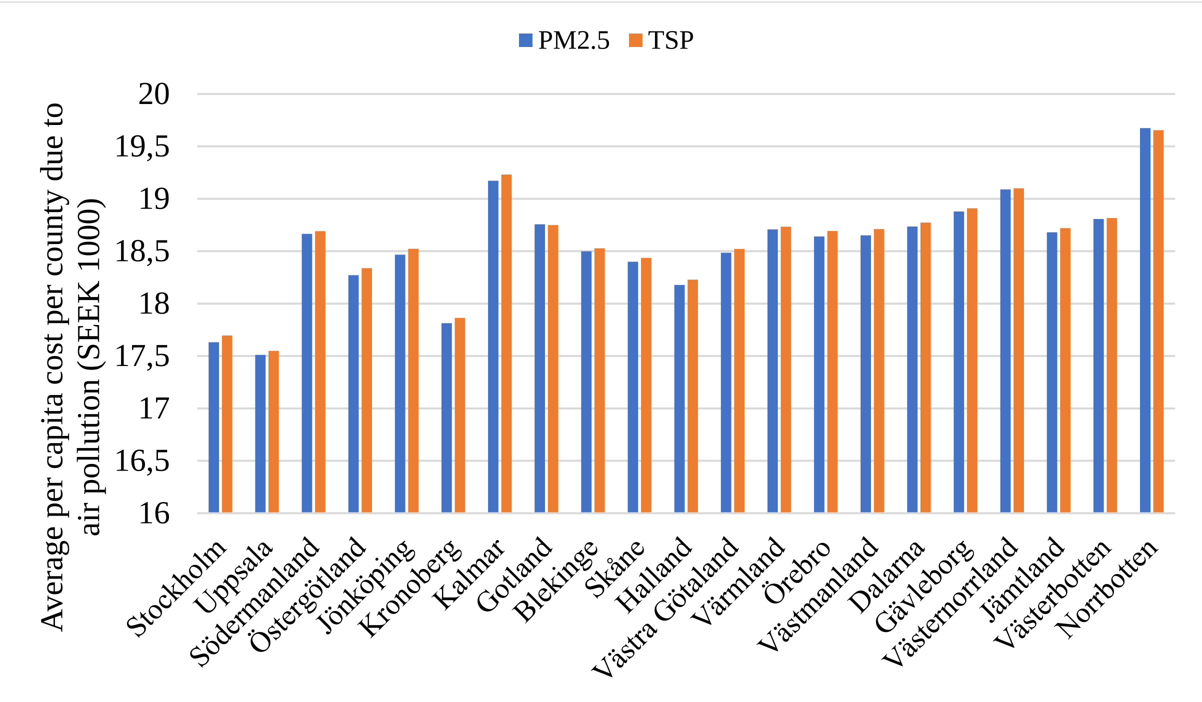

Figure 6. Average per capita cost per county due to PM2.5 and TSP

From table 10, we observe that the estimated total direct cost associated with PM2.5 and TSP is 0.11% of the Swedish GDP (measured as an average GDP of the years 2005-2016). In addition, from table 10 the indirect estimated cost due to PM2.5 and TSP is 0.10% of the Swedish GDP. This makes the total cost due to exposures to PM2.5 and TSP is around 0.21% of the Swedish GDP.

Table 10. Costs due to PM2.5 and TSP air pollutants as a percentage of GDP

	PM2.5	**TSP**	**Total**
Direct Costs	0,056%	0,056%	0,11%
Indirect cost	0,05%	0,05%	0,10%
Total economic costs	0,105%	0,105%	0,21%

These results are comparable to the results of Kubatko & Kubatko (2018) who found that the direct costs for Ukraine due to air pollution to be between 0.65–1.26% and the indirect costs to be 0.1% of the Ukrainian GDP. Gustafsson et al., (2018) had also estimated the socio-economic costs due to air pollution from NO2 and PM2.5 to be around 0.4% of the Swedish GDP of the year 2015. Sjöberg et al., (2009) also estimated the total socio-economic costs due to particulate matter as 0.893% of the Swedish GDP of the year 2005.

The results presented in this thesis have some substantial difference with Sjöberg et al., 2009 and Gustafsson et al., 2018, but one should bear in mind that Sjöberg et al., 2009 and Gustafsson et al., 2018 have accounted for morbidity, mortality and other risk factors in their estimations, while I have accounted only for morbidity. On the other hand, Quah & Boon, (2003) using the same economic cost estimations models have computed the economic cost of morbidity to be around 2.22% of Singapore GDP in 1999. Chang et al., (2012) also suggested that the socioeconomic burden of coronary heart disease due to air pollution in Korea accounts for 0.32% of GDP.

Figure 7 shows the average direct per capita cost of Sweden associated with PM2.5 and TSP over the years 2005-2016. It is observed that the average direct per capita cost due to PM2.5 and TSP over the years has exhibited a slight increasing trend in both air pollutants. Despite the declining trend of the amount of PM2.5 the direct per capita cost associated with it has shown an increasing trend over the years. While the cost and pollution trend for TSP has been parallel and increasing over the years.

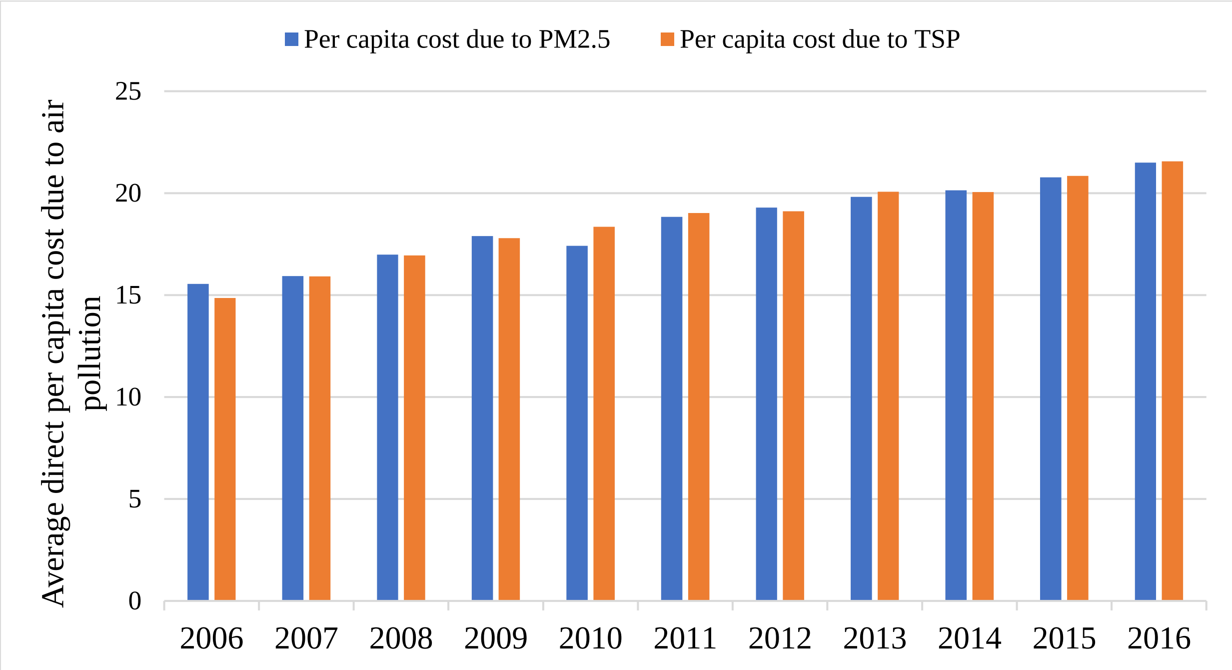

Figure 7 Average direct per capita cost due to PM2.5 and TSP, Sweden

Figure 8 presents the direct costs per county attributed to PM2.5 and TSP. It shows that Stockholm has the highest average direct cost associated with PM2.5 and TSP followed by Jönköping and Örebro. The rest of the other Swedish counties have more or less similar direct costs due to PM2.5 and TSP.

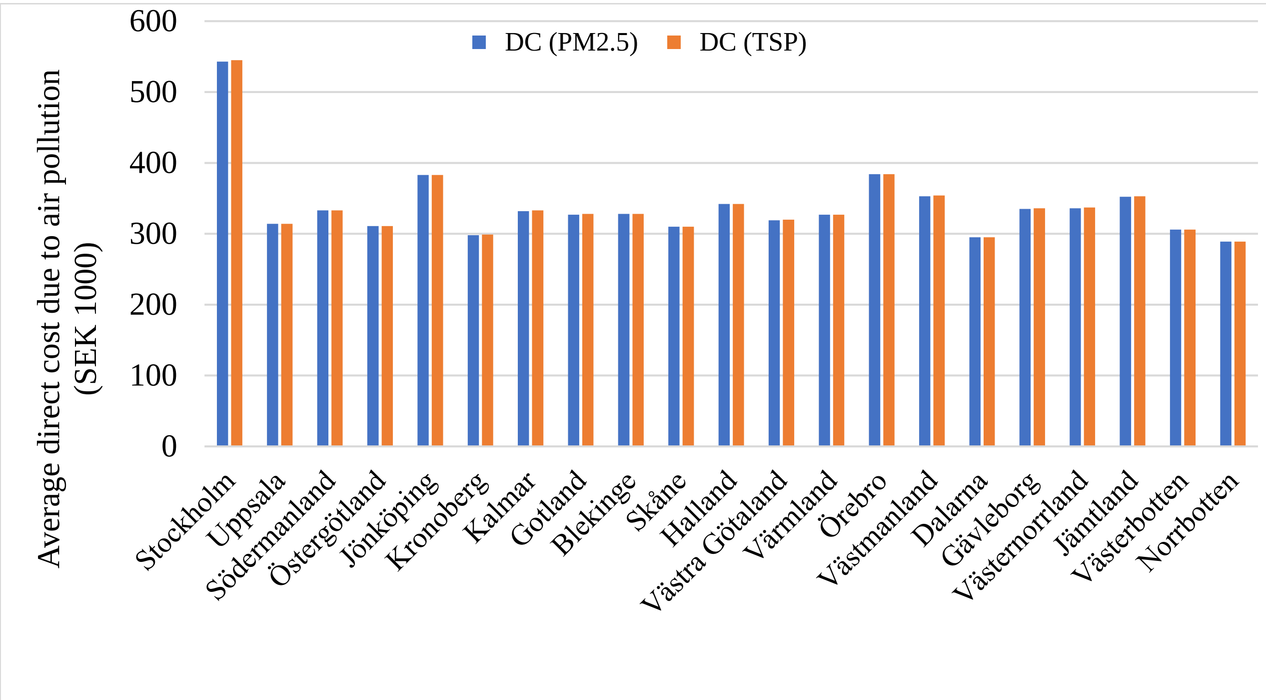

Figure 8 Average direct costs across the Swedish counties over the years (2005-2016)

Figure 9 presents the average annual indirect cost associated with PM2.5 and TSP. It also shows that over the years the average annual indirect cost have shown a slightly increasing trend, which is also shown in the per capita cost due to air pollution in figure 7.

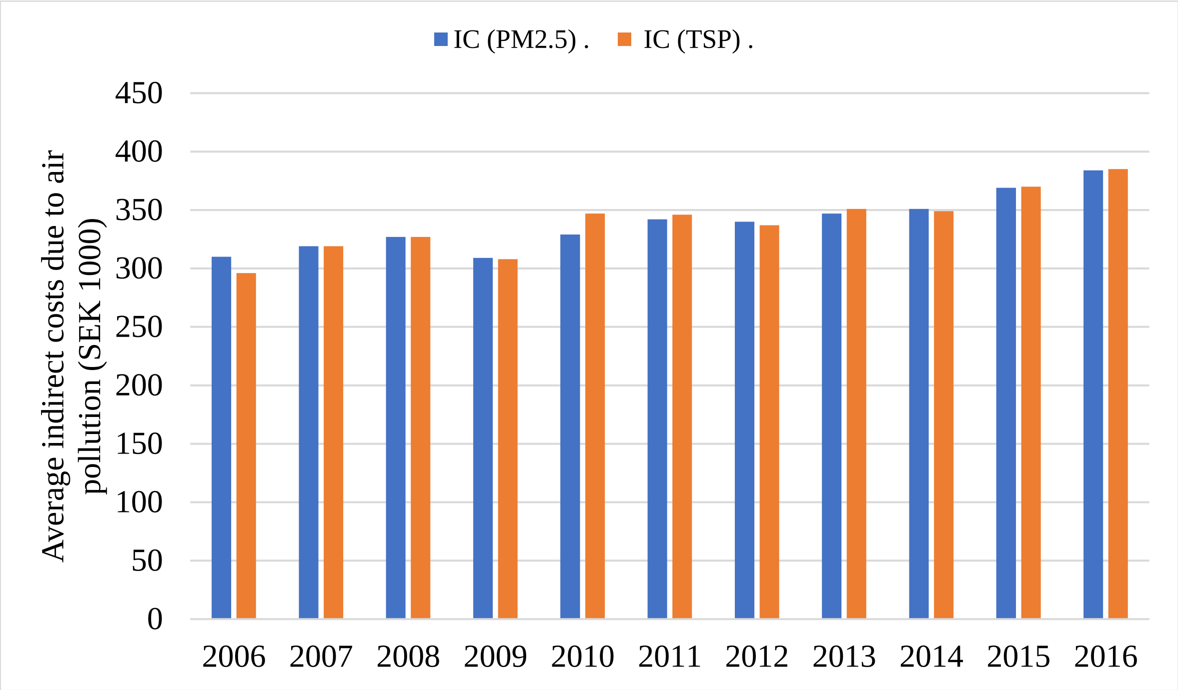

Figure 9. Average annual indirect costs in Sweden due to PM2.5 and TSP

5 Conclusions and policy recommendations

I have so far investigated the effect of air pollution (Sox, PM2.5, PM10 and TSP) on the number of patients per 100K inhabitants for all the 21 Swedish counties over the years 2005-2016. I utilized a static model of the number of patients per 100K inhabitants as the outcome variable in this thesis. Following Graff Zivin and Neidell (2013), I consider the medical care as a function of air pollution, avoidance behavior, disposable income, education, health personnel per 100K inhabitants, and population density. Based on the static model, I estimated the association of the air pollutants together with the socio-economic control variable with the number of patients per 100K inhabitants. The static model shows that there is a general linear positive association between PM2.5, TSP, SOx and number of health personnel per 100K inhabitants with the number of patients per 100K inhabitants. The model also shows that PM2.5 and TSP are significantly associated with 7 out of the 11 air pollution-related diseases. Thus, we reject the null hypothesis and accept the alternate hypothesis - exposure to the environmental air pollutants have effects on hospital morbidity

Following Kubatko & Kubatko, (2018), using a linear static model, I estimated the direct and indirect costs (opportunity cost) due to air pollution-related morbidities in Sweden. The estimated total direct cost associated with PM2.5 and TSP is 0.11% of the Swedish GDP (measured as an average GDP of the years 2005-2016). In addition, the indirect estimated cost due to PM2.5 and TSP is 0.10% of the Swedish GDP. This makes the total cost due to exposures to PM2.5 and TSP is around 0.21% of the Swedish GDP. The results suggest that on average the annual per capita cost incurred due to PM2.5 and TSP is SEK 18 558 and 18 594 respectively. The cost estimations also show that on average there is an increasing trend of the direct and indirect costs over the years 2005-2016.

Finally, the overall results of this thesis suggest that there is a need for policymakers to devise policies in the form of performance standards, design standards or other standards to meet the reduction of air pollutants. It is time to initiate policies that will encourage a further reduction in the emissions of PM2.5 and TSP. It is also required that the awareness of people to air pollution to be elevated so that people would have to improve their avoidance behavior, which in turn, could lead to a better health outcomes.

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Appendix

Table 11. Effect of air pollution on the number of patients per 100K inhabitants

VARIABLES	(1) lnTotalPatients100K	(2) lnTotalPatients100K	(3) lnTotalPatients100K	(4) lnTotalPatients100K	(5) lnTotalPatients100K
lnSOx	-0.003				-0.006
	(0.018)				(0.014)
lnPM2.5		0.042			0.142**
		(0.042)			(0.065)
lnPM10			0.064		-0.272*
			(0.047)		(0.146)
lnTSP				0.066*	0.214**
				(0.034)	(0.083)
lnDIPC	6.436*	4.938	5.954*	7.032**	5.882
	(3.273)	(3.472)	(2.940)	(3.161)	(3.968)
$lnDIPC^2$	-0.663*	-0.509	-0.610*	-0.718**	-0.599
	(0.325)	(0.348)	(0.295)	(0.316)	(0.398)
lnTotal Edu.	0.440	0.342	0.313	0.330	0.300
	(0.304)	(0.333)	(0.337)	(0.335)	(0.348)
lnTotal HP100K	0.416	0.392	0.394	0.384	0.292
	(0.301)	(0.274)	(0.308)	(0.330)	(0.291)
lnPop. density	-0.581**	-0.619***	-0.637**	-0.632**	-0.641**
	(0.228)	(0.213)	(0.242)	(0.256)	(0.232)
Constant	-13.682	-8.865	-11.205	-14.065	-10.261
	(10.220)	(11.636)	(10.456)	(10.766)	(12.904)
Observations	252	252	252	252	252
R-squared	0.476	0.482	0.485	0.496	0.521
Number of id	21	21	21	21	21
County FE	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO
Controls	YES	YES	YES	YES	YES

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

Table 12. Effect of air pollution on patients per 100K inhabitants by age groups

VARIABLES	(1) 0-4 YRS	(2) 5-9 YRS	(3) 10-14 YRS	(4) 15-19 YRS	(5) 20-24 YRS	(6) 25-29 YRS	(7) 30-34 YRS	(8) 35-39 YRS	(9) 40-44 YRS
lnSOx	0.010	0.124*	0.031	-0.054	0.015	-0.036	-0.005	0.043	0.103*
	(0.068)	(0.071)	(0.100)	(0.054)	(0.076)	(0.054)	(0.054)	(0.058)	(0.050)
lnPM2.5	0.149	0.875**	0.571*	0.899***	0.545***	0.337***	0.413**	0.567***	0.059
	(0.193)	(0.360)	(0.277)	(0.259)	(0.171)	(0.096)	(0.152)	(0.171)	(0.129)
lnPM10	-0.376	-1.114	-0.850	-1.049*	-0.756**	-0.344*	-0.391	-0.689*	0.054
	(0.444)	(0.788)	(0.729)	(0.581)	(0.315)	(0.173)	(0.360)	(0.396)	(0.242)
lnTSP	0.140	0.541	0.634	0.598*	0.593***	0.504***	0.433*	0.664***	0.261
	(0.242)	(0.388)	(0.382)	(0.318)	(0.169)	(0.112)	(0.246)	(0.222)	(0.176)
lnDIPC	5.410	-4.436	23.673*	20.337	11.942	23.538***	9.716	17.632**	14.677**
	(11.291)	(14.650)	(11.800)	(12.835)	(10.347)	(7.749)	(8.343)	(6.498)	(6.928)
$\ln DIPC^2$	-0.586	0.335	-2.391*	-2.132	-1.250	-2.340***	-0.905	-1.643**	-1.456**
	(1.162)	(1.480)	(1.178)	(1.289)	(1.034)	(0.774)	(0.833)	(0.664)	(0.694)
lnTotal Edu.	0.966	2.508	2.668**	2.816**	2.254**	1.132	-0.296	-0.227	0.974*
	(1.299)	(1.520)	(1.203)	(1.318)	(0.990)	(0.857)	(0.644)	(0.920)	(0.528)
lnTotal HP 100K	0.471	-0.185	-0.053	1.523	1.150	1.179	-0.704	-1.389	0.466
	(0.899)	(1.458)	(1.489)	(1.368)	(0.760)	(0.759)	(0.953)	(0.980)	(0.506)
lnPop. density	-0.854	-0.583	-1.005	-1.038	-1.226	-1.210*	-1.101*	-0.905	-0.285
	(0.628)	(0.989)	(0.900)	(0.746)	(0.719)	(0.630)	(0.586)	(0.575)	(0.377)
Constant	-16.193	-9.631	-84.304**	-86.809*	-56.945	-74.867***	-10.043	-28.372	-48.054**
	(45.212)	(53.399)	(37.456)	(44.636)	(33.147)	(23.911)	(24.573)	(25.245)	(22.475)
Observations	252	252	252	252	252	252	252	252	252
R-squared	0.256	0.535	0.265	0.529	0.296	0.222	0.145	0.206	0.251
Number of id	21	21	21	21	21	21	21	21	21
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO	NO	NO
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES

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

Table 13. Effect of air pollution on patients per 100K inhabitants by age groups

VARIABLES	(10) 45-49 YRS	(11) 50-54 YRS	(12) 55-59 YRS	(13) 60-64 YRS	(14) 65-69 YRS	(15) 70-74 YRS	(16) 75-79 YRS	(17) 80-84 YRS	(18) 85+ YRS
lnSOx	0.005	0.043	0.020	-0.003	-0.025	-0.039	-0.003	0.030	-0.009
	(0.040)	(0.036)	(0.031)	(0.013)	(0.023)	(0.030)	(0.019)	(0.022)	(0.017)
lnPM2.5	0.173	0.168	0.113*	0.149**	0.106	0.213***	0.149**	0.051	0.030
	(0.130)	(0.101)	(0.059)	(0.059)	(0.079)	(0.060)	(0.069)	(0.054)	(0.058)
lnPM10	-0.269	-0.402*	-0.198	-0.305**	-0.224	-0.281**	-0.286**	-0.149	-0.109
	(0.307)	(0.201)	(0.131)	(0.116)	(0.165)	(0.117)	(0.124)	(0.118)	(0.111)
lnTSP	0.221	0.395***	0.202**	0.172**	0.208*	0.234***	0.223***	0.192**	0.149**
	(0.189)	(0.133)	(0.091)	(0.074)	(0.108)	(0.069)	(0.073)	(0.077)	(0.071)
lnDIPC	20.440***	12.084**	2.699	0.876	12.674**	4.573	5.817	6.402*	2.917
	(5.285)	(4.596)	(4.799)	(4.420)	(5.155)	(4.115)	(4.363)	(3.682)	(3.905)
$\ln DIPC^2$	-2.056***	-1.191**	-0.284	-0.161	-1.309**	-0.489	-0.607	-0.663*	-0.305
	(0.529)	(0.457)	(0.484)	(0.442)	(0.518)	(0.411)	(0.436)	(0.364)	(0.390)
lnTotal Edu.	1.165**	0.095	-0.070	0.483	0.811	0.095	0.532	0.368	0.509
	(0.518)	(0.435)	(0.490)	(0.325)	(0.483)	(0.411)	(0.317)	(0.318)	(0.325)
lnTotal HP 100K	1.168**	0.065	0.232	0.826**	0.230	0.243	-0.070	0.074	-0.033
	(0.482)	(0.395)	(0.350)	(0.366)	(0.430)	(0.282)	(0.264)	(0.335)	(0.323)
lnPop. density	-0.856**	-0.650***	-0.613	-0.459*	-0.761***	-0.523	-0.572***	-0.397**	-0.644***
	(0.337)	(0.220)	(0.441)	(0.252)	(0.251)	(0.394)	(0.192)	(0.187)	(0.169)
Constant	-64.677***	-23.890*	1.947	-2.372	-31.255*	-3.352	-8.817	-9.926	-0.736
	(17.907)	(13.059)	(16.642)	(14.690)	(16.346)	(13.836)	(13.860)	(9.046)	(11.816)
Observations	252	252	252	252	252	252	252	252	252
R-squared	0.299	0.272	0.343	0.658	0.672	0.620	0.591	0.599	0.287
Number of id	21	21	21	21	21	21	21	21	21
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO	NO	NO
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES

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

Table 14. Association of air pollutants with disease types

VARIABLES	CRHD	IHD	PHD	OFHD	CVD
lnSOx	-0.022	0.004	0.075*	0.029	-0.011
	(0.190)	(0.024)	(0.038)	(0.019)	(0.030)
lnPM25	-0.271	0.159	0.262	0.202**	0.079
	(0.565)	(0.109)	(0.152)	(0.094)	(0.082)
lnPM10	1.612	-0.084	-0.788**	-0.314	-0.288**
	(1.305)	(0.187)	(0.355)	(0.185)	(0.135)
lnTSP	-1.271*	0.001	0.554**	0.244**	0.147
	(0.718)	(0.101)	(0.199)	(0.106)	(0.087)
lnDIPC	-3.447	-0.332	11.623	4.406	10.006**
	(28.903)	(6.816)	(9.511)	(5.816)	(4.047)
$lnDIPC^2$	0.320	-0.063	-1.024	-0.403	-1.053**
	(2.849)	(0.692)	(0.964)	(0.585)	(0.407)
lnTotal Edu.	-0.482	-0.550	1.007	0.035	0.944*
	(2.374)	(0.655)	(0.907)	(0.511)	(0.462)
lnTotal HP 100K	0.866	0.609	0.264	0.133	0.255
	(2.597)	(0.503)	(0.657)	(0.413)	(0.503)
lnPop. density	-0.695	-0.878**	-0.983	-1.097***	-0.777*
	(1.632)	(0.379)	(0.638)	(0.328)	(0.397)
Constant	11.108	13.955	-40.409	-4.523	-28.310**
	(88.672)	(26.251)	(36.079)	(19.696)	(13.349)
Observations	232	252	252	252	252
R-squared	0.035	0.863	0.669	0.309	0.671
Number of id	21	21	21	21	21
County FE	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO
Controls	YES	YES	YES	YES	YES

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

Table 15. Association of air pollutants with disease types

VARIABLES	DAAC	OUDCS	DRS	GU	DU	PU
lnSOx	-0.045	0.003	-0.036*	0.021	-0.085**	-0.199*
	(0.028)	(0.055)	(0.018)	(0.036)	(0.040)	(0.096)
lnPM2.5	0.047	0.154	0.099	0.245*	0.298*	0.571
	(0.108)	(0.245)	(0.084)	(0.142)	(0.143)	(0.483)
lnPM10	-0.312	-0.546	-0.289	-0.018	-0.238	-0.555
	(0.189)	(0.541)	(0.226)	(0.341)	(0.364)	(0.697)
lnTSP	0.319***	0.471*	0.281**	-0.019	0.204	0.259
	(0.103)	(0.252)	(0.114)	(0.222)	(0.260)	(0.489)
lnDIPC	22.621***	20.123*	8.869*	-6.626	2.852	-20.802
	(6.579)	(10.387)	(4.361)	(6.806)	(9.174)	(22.804)
lnDIPC^2	-2.287***	-1.833*	-0.873*	0.652	-0.300	1.828
	(0.658)	(1.041)	(0.443)	(0.673)	(0.902)	(2.266)
lnTOTAL EDUCATION	0.540	-0.558	0.531	0.097	-0.657	-0.259
	(0.699)	(1.173)	(0.499)	(0.726)	(0.783)	(1.798)
lnTotal HP per 100K	0.136	1.079	0.147	0.029	-0.906	0.994
	(0.700)	(1.068)	(0.369)	(0.666)	(0.984)	(2.110)
lnPop. density	0.415	0.323	-0.366	-1.988***	-0.648	0.548
	(0.347)	(0.923)	(0.340)	(0.448)	(0.671)	(0.947)
Constant	-60.190**	-54.459	-22.703	23.606	12.061	53.097
	(22.155)	(36.434)	(16.009)	(20.450)	(25.901)	(77.198)
Observations	252	252	252	252	252	252
R-squared	0.310	0.639	0.182	0.283	0.296	0.209
Number of id	21	21	21	21	21	21
County FE	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO
Controls	YES	YES	YES	YES	YES	YES

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