Essays on Environmental Economics

By

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Declaration

I, Eleftherios Giovanis, hereby declare that this thesis and the work presented in it is entirely my own. Where I have consulted the work of others, this is always clearly stated.

Signed:  (Eleftherios Giovanis)

Date: March 16, 2015

To my mother Anastasia Giovani and my sister Vivian Giovani

Abstract

This dissertation presents four essays in environmental economics. They address issues of environmental economics from microeconomic and program evaluation perspectives. The first essay study examines the "Clean Air Works" program on ozone concentration levels, which is operating in Charlotte area of North Carolina State. A quadruple Differences (DDDD) estimator is applied. In both cases, we find reduction in ground-level ozone levels and improvement of the air quality in the treatment group where the "Clean Air Works" program is implemented. The second essay examines the effectiveness of the vanpool programme on traffic volume, which was introduced in 2006 in York County of South Carolina State. A quadruple Differences-in-Differences (DDDD) model is applied. We find that smog alerts and the change in the ozone warning threshold in association with vanpool program lead to significant traffic volume decrease in York County. The third essay examines the relationship between air pollution and recycling using panel data from a waste municipality survey in the state of Massachusetts during the period 2009-2012. The findings support that a negative relationship between recycling rate and particulate particles in the air of 2.5 micrometres or less in size ($PM_{2.5}$) is present. This study explores the willingness to pay for (reducing) pollution in the UK. The Life Satisfaction Approach (LSA) is employed and the estimates are based on data from the British Household Panel Survey (BHPS). The effects of air pollution on individuals' happiness are estimated and their monetary value is calculated. In particular, four air pollutants are examined; sulphur dioxide (SO_2), ground-level ozone (O_3), nitrogen dioxides (NO_X) and carbon monoxide (CO). The annual monetary values for ground level ozone range between £588-£864 for a drop of one standard deviation, while the respective values for the other air pollutants range between £288-£696.

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INTRODUCTION

This dissertation is a compilation of four essays in environmental economics and delves into a wide variety of topics and unifying themes related to air pollution, life satisfaction, traffic, vanpooling and voluntary programs. In doing so, it uses a wide variety of applied economic techniques.

A central feature of modern government is its role in designing welfare improving policies to address and correct market failures stemming from externalities and public goods. The rationale for most modern environmental regulations stems from the failure of markets to efficiently allocate goods and services. In light of the health effects of ground-level ozone, a few air quality agencies have been forecasting ozone concentrations for many years to warn the public of unhealthy air and to encourage people to voluntarily reduce emissions-producing activities. From 1978 to 1997, the National Ambient Air Quality Standard (NAAQS) for ozone was 120 parts per billion (ppb). In 1997, the U.S. Environmental Protection Agency (EPA) revised the NAAQS to reflect more recent health-effects studies that suggest that respiratory damage can occur at lower ozone concentrations. Under the revised standard, regions exceed the NAAQS when the three-year average of the annual fourth highest 8-hour average ozone concentrations is above 80 ppb and in 2008 the revised standard became 75 ppb.

In the first chapter we examine the effects of the public ozone advisory and voluntary programs on ozone levels and the region of study is North Carolina State. The motivation and contribution of this study is whether the effects of “Clean Air Works” voluntary program, operating in the Charlotte Area of North Carolina State, on ozone concentration levels reduction are effective. “Clean Air Works” is a voluntary program which encourages individuals, employees and employers to adopt practices that can improve air quality, such as public transit, carpool, vanpool and teleworking among others. In addition, whether ozone smog alerts are more effective under this program is explored in this study. Finally, the effects on ozone concentrations levels coming from the reduction in the warning threshold from 80 particles per billion (ppb) to 75 ppb, which took place in 2008, are established. For this purpose a quadruple Differences (DDDD) estimator is applied. In both cases, we find reduction in ground-level ozone levels and improvement of the air quality in the treatment group where the "Clean Air Works" program is implemented. This study suggests that voluntary programs can help to clean the air and improve the public health.

The second chapter follows an identical approach and methodology, but in that case the effects of the vanpool program on traffic are examined. Regarding traffic and air pollution, commuting to and from work is a primary cause of increased traffic congestion and air quality problems in many areas across the United States. Reducing the number of cars commuting during rush hour can reduce traffic and improve air quality. The aim of vanpool program is to allow commuters to ride together in a van, particularly in areas where public transportation is not provided. This type of program provides employees who commute via transit, car or carpool, with transportation home in the event of a personal emergency or unscheduled overtime.

The majority of the studies have examined the effects of ozone forecasts or ozone action days on traffic volume; however the impact of vanpool programs related to ozone forecasts has not been explored yet. Thus, the purpose and contribution of second chapter is to examine the effectiveness of the vanpool programme, introduced in 2006 in York County of South Carolina State, on traffic volume. In addition, this study investigates whether the smog alerts, triggered by the Environmental Protection Agency (EPA), are more effective on traffic volume under the vanpool programme. Finally, the effects of the warning threshold, which was reduced from 80 parts per billion (ppb) to

75 ppb in 2008, are explored. The study period is 2004-2010. A quadruple Differences-in-Differences (DDDD) model, similar to the first chapter, is applied. We find that smog alerts in association with the vanpool program lead to negative and significant decrease on the traffic volume in York County.

The third chapter is differentiated from the previous two in the meaning that the effects of recycling on air pollution are explored. The majority of the environmental economics literature pays attention to the waste management services and cost structure. Because the relationship between air pollution and recycling has been neglected in the previous economic studies the contribution of this study is the examination of this relationship using panel data from a waste municipality survey in the state of Massachusetts during the period 2009-2012. In addition, the analysis considers economic factors, as unemployment rate and income per capita, meteorological variables, as well as, it accounts for additional municipality characteristics, such as population density and trash collection services. The approach followed is a fixed effects model which controls for stable time invariant characteristics of the municipalities, thereby eliminating potentially large sources of bias. The findings support that a negative relationship between particulate particles in the air of 2.5 micrometres or less in size (PM2.5) and recycling rate is present. More specifically, the results show that for a one percentage increase in recycling rates the $PM_{2.5}$ is reduced by 0.021-0.024 per cent or by 0.0017-0019 micrograms per cubic meter ($\mu g/m^3$). In addition, an inverted U-shaped curve of the relationship between income per capita and pollution is presented.

The fourth chapter examines the relationship between happiness and air pollution using the Life Satisfaction Approach (LSA). Air pollution has negative effects on health outcomes and increases death probability. However, policies to reduce pollution are often hardly fought on the ground of their high financial costs. It is thus crucial to have reliable estimates of the public willingness to pay for a cleaner environment. Thus, the motivation of this study is to get precise estimates. The contribution is that the analysis relies on detailed micro-level data, using grid references. Using BHPS' respondents' post codes of residence expressed on grid references coordinates allows us to map air pollution to individuals with high precision. The results show that the O_3 and SO_2 present the strongest negative effects on happiness followed by CO and NO_X. The annual monetary values for ground level ozone range between £588-£864 for a drop of one standard deviation, while the respective values for the other air pollutants range between £288-£696. Overall, the results in this chapter demonstrate that air pollution has direct and significant effects on individuals' welfare and that a substantive tradeoff between income and air quality is presented.

Chapter One

Evaluation of Ozone Smog Alerts on Actual Ozone Concentrations: A Case study in North Carolina

Eleftherios Giovanis[1]

Abstract

Ground-level ozone is an important pollutant regulated under the Clean Air Acts that affects respiratory morbidity, decreases lung function, and negatively affects those with existing respiratory conditions like asthma. This study examines the "Clean Air Works" program on ozone concentration levels, which is operating in Charlotte area of North Carolina State. "Clean Air Works" is a voluntary program which educates people about the negative effects of air pollution on health. Moreover, this program encourages people to reduce air pollution by using voluntarily alternative transportation modes, such as carpooling and public transit, especially when a smog ozone alert is issued. The contribution of this study is that it examines three effects: The effectiveness of the "Clean Air Works" program and whether ozone smog alerts are more effective under this program. Finally, the effects on ozone levels coming from the change in the warning threshold from 80 particles per billion (ppb) to 75 ppb, which took place in 2008, are established. For this purpose a quadruple Differences (DDDD) estimator is applied. In both cases, we find reduction in ground-level ozone levels and improvement of the air quality in the treatment group where the "Clean Air Works" program is implemented. In addition, the air quality is improved when smog alerts are associated with the program. Finally, taken additionally into consideration the change of the threshold at 75 ppb the air quality is improved by 1.5 ppb in the treatment group relatively to the control group. This study suggests that the ozone warning system associated with voluntary programs can help to clean the air and improve the public health.

Keywords: Air Quality, Clean Air Works, Differences-in-Differences, Ozone concentrations, Quadruple DDDD, Regression Discontinuity Design, Smog alerts

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1. Introduction

Air pollution has long been recognized as a negative externality. Making regulations concerning ozone is an area of increasing importance. Environmental policy makers around the world increasingly rely on voluntary programs to improve environmental quality (Cutter and Neidell, 2009). For example, Moretti and Neidell (2011) provide direct evidence that people respond to information about air quality. In particular, when smog alerts are issued, attendance at major outdoor facilities in Los Angeles decreases by as much as 13 per cent. Most studies examine the effects of ozone forecasts to public health, traffic volume and transportation mode choice behaviour.

This paper studies the effectiveness of policy mechanisms in the context of the "Clean Air Works" program in the Charlotte Area of North Carolina State, which aims to motivate individuals to follow practices that reduce ozone pollution, especially on the smog alert days. The study period is 2000-2010. The contribution of this study is that the effectiveness of this program along with smog alerts is examined. In addition, this is the first study which establishes the effects of the change in the warning threshold from 80 parts per billion (ppb) to 75 ppb in 2008.

"Clean Air Works" is a program launched in spring of 2006, established in Charlotte Area of North Carolina and it is a collaboration of the Regional Air Quality Board, the City of Charlotte, Mecklenburg County, Charlotte Area Transit System (CATS), the Charlotte Chamber of Commerce, the Centralina Council of Governments, and the Catawba Regional Council of Governments. The purpose of this program is to educate employees about the effects of air pollution on public health and to provide a low or no cost transportation benefit. The purpose is to avoid federal penalties from not meeting air quality standards, as the imposition, by EPA, of $8,300 (in 2010 prices) per ton penalties on major sources of air pollution.

Partners of "Clean Air Works" have a variety of options from which to choose: from offering employees commute alternatives, making changes in the organization's operations and maintenance practices, creating a combination of programs based on individual business needs. "Clean Air Works" has developed a range of tools and policies, like carpooling, vanpooling and teleworking. Therefore, partners of "Clean Air Works" encourage people to use these tools when a smog alert is issued. In this case the treatment group includes counties participating in the program, while the control group contains the counties that do not participate in the program. The criteria of using the specific counties as control group are discussed in data section. The second aim is to establish whether the ozone smog alerts are more effective under the "Clean Air Works" programme. The ozone forecasts are based on daily frequency and the forecast season is from May 1st through September 30th. The third aim is to examine the impact of the change in the ozone standard issued by the Environmental Protection Agency (EPA).

In order to identify those effects a quadruple Differences (DDDD) estimator is applied. The results show a reduction on the ozone levels after the implementation of the "Clean Air Works" Project. Additionally, the ozone levels on alert days were reduced after the change of the threshold in both treatment and control. The air quality has been improved in the treatment group with the implementation of the program reducing the difference in ozone concentration levels by 1.3 ppb. In addition, the smog alerts are effective under the program regime where the above-mentioned difference becomes 1.8 ppb. Furthermore, the differences of ozone levels between the treatment and control groups are additionally decreased after the change in ozone warning threshold, by around 1.5 ppb when the program is implemented and it is associated with smog alerts. As such, information on air pollution does not seem to significantly reduce pollution level unless a program like "Clean Air Work", which facilitates steps reducing pollution, is in place.

The results are robust regarding the DDDD validity. The test for the common or parallel trend is accepted. More specifically, the common trend assumption states that changes in output, average ozone concentration levels in this case, for those treated if untreated would have been equal to the observed changes in output for the control group. Common trend assumption implies that in absence of treatment the treated and the controls would have had parallel trend paths. Another issue is the possible serial correlation. Many papers which apply differences-in differences (DID) strategy use data for many years before and after the implementation of a policy. The variables of interest in many of these setups only vary at a group level (ie. state level in the study by Card and Krueger, 1994) and outcome variables are often serially correlated. Thus, using conventional standard errors often severely understate the standard deviation of the estimators. In order, to account for serial correlation, the clustered standard errors on air monitoring stations are obtained as suggested by Bertrand et al. (2004) and where the monitoring level variation is examined.

The structure of the paper is as follows. In section 2 the literature review is provided. Section 3 describes the environmental policy and the "Clean Air Works" project, while section 4 reviews the methodology of the quadruple DID model used in this study. Section 5 presents the data, and the research sample used in the estimations, while in section 6 the empirical findings are reported. In the last section the general conclusions of the empirical findings are discussed.

2. Literature review

This section presents and discuses previous literature related to the current study. Initially, the studies examined the effects of public advisory programs on traffic are presented. These studies are related because “Clean Air Works” project encourages individuals to follow practises that reduce air pollution, such as public transit and carpooling, which affect the traffic pattern and resulting in changes on the ozone concentration levels.

One of the public advisory programs explored in previous studies is the “Spare the Air” (STA) program. “Spare the Air” was established by the Bay Area Air Quality Management District in order to educate Bay Area residents about air pollution and to encourage them to change their behaviour to improve air quality. As part of the Spare the Air program, the residents are asked to reduce pollution by making clean air choices every day; from walking and biking more often, to reducing energy consumption at home. Spare the Air days are declared for days in which levels of ground-level ozone are predicted to exceed the EPA’s federal health-based standard: the air quality index (AQI) over 100. Moreover, on a Spare the Air day, Bay Area participants are asked through radio and television announcements to reduce their driving. This program is similar to Clean Air Works program examined in this study. Ozone warning announcements encourage people to reduce driving or using public transit and various kinds of ridesharing, such as carpool and vanpool, or using teleworking.

Schreffler (2003) focused on “Spare the Air” advisory and voluntary program by conducting a small telephone survey in the Bay Area that requested daily travel activities. Schreffler (2003) used data over two summer ozone seasons in Sacramento, allowing researchers to compare the travel behaviour of the same individuals on both Spare the Air and regular, summer days and of Spare the Air participants and non-participants. More specifically, the participants is a group of drivers who said that they purposely reduced trips because of Spare the Air, while non-participants is a control group of drivers who did not respond to the Spare the Air (STA) message. Schreffler (2003) found a statistically significant 4.8 per cent reduction in trips. The 4.8 per cent reduction in trips resulted in an emission reduction of 1.04 tons of ozone precursors.

A similar work to the current study is by Cutter and Neidell (2009), who examined the effects of “Spare the Air” advisory program in the San Francisco bay area using a Regression Discontinuity (RD) design. More specifically, they compared the bay area, where the STA alert is issued, and the South Coast area, where the STA program is not applied. Cutter and Neidell (2009) estimated a regression discontinuity approach using a sample of observations within 2 and 1 parts per billion (ppb) of the limit for a STA call and they showed a statistically significant drop in vehicle usage of between 2,000 and 2,300 per day. Welch et al. (2005) examined the impact of ozone advisories on hourly public transit in Chicago, Illinois, and found mixed results. The overall effect of ozone action days on ridership is not significant, but there are statistically significant changes in hourly ridership pattern. Additionally, their findings show that ozone advisories systematically alter the travel behavior of a small proportion of Chicago area travelers making it possible to conclude that pollution advisories have the potential to affect transportation choice and thereby contribute substantially to voluntary reductions in ozone emissions. More specifically, ridership increases during the hours of 9–11 am and 5–9 pm on smog alert dates representing 0.03–0.13% hourly vehicles miles of travel reduction in Chicago traffic. On the other hand, Cummings and Walker (2000) examined a similar voluntary program in the Atlanta metropolitan area on hourly traffic volumes and found statistically insignificant effects.

Friedman et al. (2001) examined the changes in transportation choices and the effects in asthma hospitalizations during the 1996 Olympic Games in Atlanta. Atlanta's strategy included the development and use of an integrated 24-hour-day public transportation system, the addition of 1,000 buses for park and ride services, altered downtown delivery schedules, and public warnings of potential traffic and air quality problems among others. The authors compare the 17 days of the Olympic Games, with a baseline period of four weeks before and four weeks after the Olympic Games but do not have a control group. The authors found that the number of asthma emergency care visits and hospitalizations decreased from 4.23 events per day during the baseline period to 2.47 events per day during the Olympic period, a 41.6% overall decrease. Additionally, this reduction was even stronger during the critical morning period.

Even though the study by Friedman et al. (2001) examines the effects of public warnings on traffic and air quality, a control group is missing from the analysis; thus the effects are hindered by its absence. In addition, the previous studies examined the effectiveness of public advisory programs on traffic volume and ridership pattern; but the change in the ozone warning threshold has not been explored. Thus, the current study adds to the literature by applying a quadruple DID and examining the effectiveness of the "Clean Air Works" voluntary program associated with smog alerts. Moreover, the change of the warning threshold proposed by Environmental Protection Agency (EPA) is explored. Thus, the motivation of this study is to examine whether the smog alerts associated with additional incentives provided by the "Clean Air Works" are more effective for the air quality improvement. More specifically, Cutter and Neidell (2009) argue that the STAs warnings are not enough to improve significantly the air quality, if these are not associated with additional incentives, such as those provided by the program examined in this chapter.

In addition, the weather data have been neglected in the previous studies, with the exception of the study by Welch et al. (2005) who used various weather conditions, such as temperature, days with light and heavy rain and extreme weather including thunderstorms and other extreme conditions. Ground level ozone is formed in the air by the photochemical reaction of sunlight, high temperature and nitrogen oxides (NO_x), facilitated by a variety of volatile organic compounds (VOCs), which are photo-chemically reactive hydrocarbons (Crutzen, 1974; Derwent et al., 2003; Pudasainee et al., 2006). Thus, the regressions in this study control for solar radiation and temperature. In addition, wind speed and direction are important factors for ozone, as previous researches found relationship between these weather conditions and ground level ozone (Agudelo-Castaneda et al., 2013; Figueiredo et al., 2013). More specifically, wind speed cleans the air in an area and contributes to how quickly pollutants are carried away from their original source. However, strong winds do not always disperse the pollutants, as wind can transport pollutants to a larger area, such as the smoke from forest fires (Jacob et al., 1993; Baertsch-Ritter et al., 2004; Camalier et al., 2007; Dawson et al., 2007). Pugliese et al., 2014 found that areas are affected more by the ground level ozone when the wind speed is less than 120 km. Ozone also depends on wind direction. The wind direction plays a significant role in how much ozone is transported from one place to another (Jammalamadaka and Lund, 2006). Witcraft et al. (2006) found that one of the reasons explaining the low ozone levels in the Triad area in North Carolina during July of 2015 it was the dominant west to west-south wind direction.

Other studies include the exploration of the effects of pollution on infant mortality and yield mixed results. These studies are presented for the following reasons: To confirm and examine the effects of ozone reduction on mortality caused by the program and the smog alerts. In addition, the current study examines the effects of the air pollution reduction, caused by the "Clean Air Works" program, on the total, infant and elder (60 years and older) deaths. Woodruff et al. (1997) found that infants with high exposure (more than 170 micrograms per m^3) to particulate matter smaller than 10 micrometers (PM_{10}) are more likely to die in the post neonatal period. More specifically infants are categorized as having low, medium, or high PM_{10} exposure depending on whether their 2-month mean exposure was in the bottom one-third, middle one-third, or top one- third of the range of exposures. Overall post-neonatal mortality increased with increasing PM_{10} levels, from 3.1 in the low pollution category to 3.7 in the high category. Normal birth weight infants with high PM_{10} exposure were 45% more likely to die of respiratory causes than normal birth weight infants with low exposure. Lipfert et al. (2000) found negative effects of county-level pollution measures on infant mortality, but the PM_{10} risks appear to be higher for babies of smoking mothers. Currie and Neidell (2005) examined the effects of Carbon Monoxide (CO) and PM_{10} on infant mortality using data from California Birth Cohort files for 1989 to 2000. Their estimates imply that reductions in CO and PM_{10} over the time period they study saved over 1,000 infant lives in California alone. Based on the findings by Currie and Neidell (2005) and the estimates found in the current study the number of lives saved from the air quality improvement, under the "Clean Air Works project" associated with the change of the threshold and ozone smog alerts are presented in the results section.

3. Environmental Policy

3.1 Smog Alert and Ozone Forecasts

Air quality forecasts are provided by the EPA, which sets the National Ambient Air Quality Standards (NAAQS). The forecasts are published one day before by Division Air Quality ozone forecast Centre. This Air Quality Index ranges from 0 to 500 ppb and is categorized into the following: 0–50, good; 51–100, moderate; 101–150, unhealthy for sensitive groups; 151–200, unhealthy; 201–300, very unhealthy; and 301–500, hazardous (Environmental Protection Agency, 2008). From 1997 the national standard was set up at 80 ppb, corresponding to 111 on the revised AQI scale. In 2008 this standard was reduced to 75 ppb, corresponding to 100 on the revised AQI. EPA revised the threshold level to provide increased protection for children and other "at risk" populations against an array of ground-level ozone related adverse health effects that range from decreased lung function and increased respiratory symptoms to serious indicators of respiratory morbidity including emergency department visits and hospital admissions for respiratory causes (Environmental Protection Agency, 2008).

An initial idea of the magnitude on ozone concentration levels, by reducing the threshold by 5 ppb, would be a similar reduction on the ozone levels. This is initially confirmed by the data. More specifically, the average ozone concentration levels are 54 and 49 ppb before and after the change in threshold respectively, for both control and treatment group examined in this study. Secondly, the new air quality standards defined by the change of the warning threshold imply stricter and tighter regulations associated with fee penalties for violation of these standards. Thus, the local governments of the counties are responsible to take additional measures and policies to improve the air quality and avoid these costs from the fee penalties.

The air Awareness Program has been established in North Carolina in 1997. In particular, Air Awareness Program is a public outreach and education program of the North Carolina Division of Air Quality (DAQ). U.S. Environmental Protection Agency (EPA) has designated the DAQ as the lead agency for enforcing federal laws and regulations dealing with air pollution in North Carolina. The goal of the program is to reduce air pollution though voluntary actions by individuals and organizations.

Ozone forecast is published and distributed through local media (television, radio, and newspaper) to public. The ozone forecast gives the public important information about the next day's air quality in their area and how their health may be affected. The forecast is also displayed on the NCDAQ (North Carolina Division of Air Quality) web page. The ozone forecasts are expressed in the air quality index described before, defining various levels of ozone concentrations, as healthy and moderate to unhealthy. A smog alert is issued in the case where the forecast passes the threshold 80 ppb and 75 ppb for periods 2000-2007 and 2008-2010 respectively. In that case the North Carolina Air Awareness Program utilizes a wide range of web and media outlets to broadcast the message to the general public. These include state-wide radio messages covering open burning, clean air tips, and much more. Through both local coordinators and state representatives, the program regularly exhibits at health, environmental, and state fairs and festivals. Public information is distributed through the program website, which is available at NCDAQ web page or the individuals can call the toll-free air quality hotline. Information may also be obtained by sending enquiries to specific email address.

3.2 Clean Air Works Program

"Clean Air Works" program launched in March of 2006 with the primary purpose of testing what organizational approach and implementation elements and methods will produce quantifiable reductions in ozone-forming pollutants above those obtained through efforts before its implementation. The aim of the program is to achieve air pollution reductions from mobile, non-road mobile and operational sources through promotion of alternate modes of transportation, such as carpooling, vanpooling, telecommuting, riding transit, walking and biking. Moreover, the program aim to improve air quality from changes in business operations e.g. cleaner fleets, delaying or postponing high-emission activities, such as construction work, lawn maintenance. In the beginning of the program around 90 largest companies secured participation in the program representing a minimum of 120,000 employees. The number of companies and partners has been increased at 118 in 2010. The incentives and practises of the program include trip reduction strategies, such as vanpool and public transit financial incentives, educational programs to employers and employees. Other incentives include alternative scheduling, such as flextime, where an employee can schedule arrival and departure times within an eight-hour day to best suit personal schedules on a daily basis, as well as, compressed work weeks, whereby an employee works more hours per day, but fewer days per week. Other incentives and practices include the postponing of high-emission activities in manufacturing, wherever possible, during the ozone warning days.

4. Methodology

4.1 Quadruple Differences-in-Differences Model

The ozone forecasts started with the Clean Air Act in 1997. None of the areas were considered as non-attainment based on ozone standards and the threshold of 84 ppb, which was applied before 1997. More precisely, the Clean Air Act and Amendments of 1990 defines a “non-attainment area” as a locality where ozone levels persistently exceed National Ambient Air Quality Standards, which standards have been presented in section 3.1. However, based on the ozone standard and the threshold of 80 ppb introduced in 1997, 11 areas encompassing over 30 counties are designated non-attainment; i.e. they do not satisfy the clean air regulations (Map 1). Grey zones in Map 1 represent the regions with ozone forecasts.

The counties treated are Lincoln, Mecklenburg, Rowan and Union in Charlotte Area, while the counties used as control group are the following: Forsyth, Rockingham, and Guilford Counties in Triad area, Raleigh County in Triangle area, Cumberland County in Fayeteville area, Buncombe County in Asheville area and Caldwell County in Hickory area. One of the reasons for choosing the treated and non-treated counties is that all of them are considered as “non-attainment areas”. Additionally, these counties share common demographic and economic characteristics. In table 1 the control and treated counties and the area they belong are presented, while in table 2 the date of the events is reported. As it is shown in table 2 EPA established the ozone standard and warning threshold at 80 ppb in 1st July of 1997. In 1st March, 2006 the “Clean Air Works” program has started to be implemented. In 27th May of 2008 the change of warning threshold from 80 ppb to 75 ppb, established by EPA, took effect.

Then a simple set-up of DID is presented in order to show the main ideas and problems of this strategy. The treatment variable, denoted by *treat* in the case examined, is binary, taking value 1 for the treatment group and 0 for the control. There are measurements of the various variables in two time periods, denoted here as *program*. *Program* zero indicates a time period before the treatment (pre-treatment period) and *program* one indicates a time period after the treatment took place (post-treatment period). Assuming that the treatment happens between the two periods means that every member of the population is untreated in the pre-treatment period. Thus the main point of interest is to discover the mean effect of switching *treat* from zero to one on some outcome variables, which is ozone levels in the study examined.

The model examined in this study is a quadruple DDDD. Difference-in-differences analysis controls for any omitted factors that influence ozone concentration levels differently for the treatment and control groups and that are constant across time. The important benefit of the quadruple differences analysis is that, in addition to controlling for those factors, it will also remove any omitted factors that influence ozone levels differently across time for counties in the treatment and control groups. The key variable in a DID strategy is frequently the outcome of interest in a period before the treatment took place. Thus, DID is appropriate in this study which allows us to evaluate the impact of the "Clean Air Works" program associated additionally with smog alerts and the change of the ozone warning threshold. The DDDD regression has the following form:

$$\begin{aligned}
&ozone_{i,j,k,t} = \beta_1 treat_{i,j,k,t} + \beta_2 program_{i,j,k,t} + \beta_3 warning_{i,j,k,t} + \beta_4 threshold_{i,j,k,t} + \\
&\beta_5 treat_{i,j,k,t} * program_{i,j,k,t} + \beta_6 treat_{i,j,k,t} * warning_{i,j,k,t} + \beta_7 treat_{i,j,k,t} * threshold_{i,j,k,t} + \\
&\beta_8 program_{i,j,k,t} * warning_{i,j,k,t} + \beta_9 program_{i,j,k,t} * threshold_{i,j,k,t} + \\
&\beta_{10} warning_{i,j,k,t} * threshold_{i,j,k,t} + \beta_{11} treat_{i,j,k,t} * program_{i,j,k,t} * warning_{i,j,k,t} + \\
&\beta_{12} treat_{i,j,k,t} * program_{i,j,k,t} * threshold_{i,j,k,t} + \beta_{13} program_{i,j,k,t} * warning_{i,j,k,t} * threshold_{i,j,k,t} + \\
&\beta_{14} treat_{i,j,k,t} * program_{i,j,k,t} * warning_{i,j,k,t} * threshold_{i,j,k,t} + W_{i,j,t} + \mu_i + l_j + z_k + \theta_t + \varepsilon_{i,j,k,t}
\end{aligned} \tag{1}$$

The dependent variable *ozone* stands for actual ozone levels in air monitoring station *i*, located in county *j*, in forecasting zone-region *k* and in time *t*. *Treat* denotes whether the counties belong to the *treatment* or control group, *program* takes value 1 since the "Clean Air Works" has been implemented on 1st March of 2006 and after and 0 otherwise. *Warning* is a dummy variable taking value 1 whether there is a smog alert and 0 otherwise, while *threshold* denotes the change of smog alert threshold from 80 ppb to 75 ppb and takes value 1 for 27th May of 2008 and after and 0 otherwise. The model controls for the day of the week, month, year, counties, ozone regions and weather conditions ($W_{i,j,t}$), such as temperature, wind speed, wind direction and solar radiation. Set (μ_i) denotes the monitoring station-fixed effects, (l_j) is a set of county fixed effects, (z_k) expresses the ozone forecasting zones-regions fixed effects and θ_t is a set of time-fixed effects. Finally, $\varepsilon_{i,j,k,t}$ expresses the error term. Clustered ozone monitoring sites are considered for robust standard errors. The model controls for time-invariant country which can determine the ozone level in the absence of the treatment. In addition, regression (1) control for year effect which is common among counties, which captures common shocks as the Great Recession, which caused by the housing bubble in August of 2007 and its effects became apparent in the beginning of 2008.

The interaction term *treat*program* is the diff-in-diff (DD) estimator which shows the effectiveness of the "Clean Air Works" project, while the interaction term, *treat*program*warning* is the DDD estimator which shows whether the smog alerts are more effective, on ozone levels reduction, under the "Clean Air Works" program. Finally, the interaction term *treat*program*warning*threshold* is the DDDD estimator which establishes the effectiveness of the smog alert threshold change in 2008 at 75 ppb. Therefore using the quadruple DDDD it becomes feasible to examine various effects.

4.2 Test of the Quadruple DDDD Model Validity

In this section the methodology followed for testing the validity of the DID model is discussed. Then in the results section the robustness checks are presented. More specifically, the key assumption for any DID strategy, the so-called "Common" or "Parallel" Trend Assumption. This assumption states that the differences in the expected potential non-treatment outcomes (ozone levels) over time are unrelated to belonging to the treated or control group in the post-treatment period. It implies that if the treated had not been subjected to the treatment, both treatment and control groups would have experienced the same time trends. Moreover, DID controls for other factors affecting outcome in both groups around the same time, such as the great recession which affected both groups and it is not a local effect.

Regarding the DDD, the assumption is that in absence of the treatment, the average difference in ozone levels for the treatment group between the smog alert and non-smog alert days is the same as the average difference in the ozone levels for the control between the smog alert and non-smog alert days. Thus, the triple DDD assumes that a common trend is thought to exist across the smog alert days and non-smog alert days in the two groups. In a similar fashion the quadruple DDDD is defined, which is the difference between the triple DDD for treatment and control groups, considering additionally the change in the ozone warning threshold.

In order to test the parallel or common trend assumption is to place placebo dummies before the treatment. If the effect captured by the "Clean Air Works" program were not causal, we would expect the coefficient on years prior to the program implementation to be as large and significant as that in which the program occurs. More precisely, the DID is estimated assuming that the "Clean Air Works" project took place before 2006.

In particular, we assume that the policy took place in 2004 instead of 2006 and the basic DD model is estimated using data from 2000-2005:

$$ozone_{i,j,k,t} = \beta_1 treat_{i,j,k,t} + \beta_2 program_{i,j,k,t} + \beta_3 treat_{i,j,k,t} * program_{i,j,k,t} + \\ W_{i,j,t} + \mu_i + l_j + z_k + \theta_t + \varepsilon_{i,j,k,t} \tag{2}$$

The reason why in model (2) only the double DID is examined is because the only difference between the control and treated group is the implementation of the "Clean Air Works" program. On the other hand the smog alert advisory program and the change of threshold are applied in both groups. Thus, it is only necessary to test the validity of the double DID, which refers to the effectiveness of the "Clean Air Works" program examined and which differentiates the treatment and control groups. Moreover, the results remain robust whether the placebo test is applied in other years instead of 2004.

The second test of the DID validity is to include a set of lags and leads into the basic DID model (2) in order to examine the dynamics of the program and to test whether the leads and lags of the treatment are significant or not. Including leads into the DID model is a way to analyse pre-trends, while lags can be included in order to analyse whether the treatment effect changes over time after the implementation of the "Clean Air Works" program. Regression (2) is written as:

$$ozone_{i,j,k,t} = \beta_1 treat_{i,j,k,t} + \beta_2 program_{i,j,k,t} + \sum_{p=0}^{m} \beta_{-p} D_{i,j,k,t-p} + \sum_{p=1}^{q} \beta_{-p} D_{i,j,k,t+p} + \\ W_{i,j,t} + \mu_i + l_j + z_k + \theta_t + \varepsilon_{i,j,k,t} \tag{3}$$

Regression (3) is testing for causality in the framework of Granger (1969) and $D_{i,j,k,t}$ is defined as the interaction term *treat*program* defined in regressions (1) and (2). More specifically, Granger causality test is a check on whether past $D_{i,j,k,t}$ predicts the ozone while future $D_{i,j,k,t}$ does not, conditional on county and year effects. The sums on the right hand side of equation (3) allow for m lags, (β_{-1}, β_{-2},.....,β_{-m}) defining the post-treatment effects and q leads ((β_{+1}, β_{+2},.....,β_{+q}) defining the anticipatory effects (Angrist and Pischke, 2008). In addition, the lagged variables are of substantive interest, because the causal effects might grow, fade or remain stable through time.

5. Data

The data for forecasting ozone concentrations have been retrieved from the North Carolina Department of Environment and Natural Resources (http://daq.state.nc.us). Ozone forecasts are made daily during the ozone forecast season, from May 1st through September 30th , by meteorologists who use a set of criteria from historic meteorological data, ozone measurements, and ozone prediction models to make these predictions. When they forecast an Ozone Action Day, the North Carolina Division of Air Quality contacts officials in the affected area notify local media, government, business, and industry. The actual ozone concentrations are measured at county level, while the ozone forecasts are assigned on regions – group of counties. More specifically the regions are defined as in map 1, which are the Asheville, Hickory, Triad, Triangle, Charlotte, Rocky Mount and Fayetteville.

The meteorological data have been kindly provided by the State Climate Office of North Carolina (www.nc-climate.ncsu.edu). The weather data used in the estimates are the average daily temperature, wind speed, wind direction and solar radiation. A negative association between wind speed and actual ozone levels is expected, while a positive relationship between temperature, solar radiation and observed ozone concentrations is anticipated. The data are based on daily frequency and the period examined is 2000-2010 and during the ozone forecast period which is between months May-September.

In table 3 the summary statistics for actual ozone concentrations are reported, while in table 4 the exceedance days over periods 2000-2005 (before Clean Air Works program implementation), 2006-2007 (when Clean Air Works program is implemented and before the change in threshold) and 2008-2010 (when the threshold is set up at 75 ppb). Exceedance days are defined as the days where the actual ozone concentration levels are higher than the smog alert threshold. In the regression analysis the ozone concentration levels expressed in parts per billion are used. It can be observed that the number of exceedance days has been reduced, especially in Charlotte and Triangle areas. In addition, the number of exceedance days for the treatment and control group is provided in table 4. Based on tables 3 and 4 the conclusion is that the ozone levels have been reduced in the period 2008-2010. It should be noticed that the exceedance days, regarding the various areas reported in table 4, refer to counties, which are not included in the control and treatment groups.

In figure 1 the distribution of actual ozone concentration levels in parts per billion (ppb) over periods 2000-2007 and 2008-2010 is presented. Based on this figure a clear drop in ozone concentrations is observed, where the average ozone levels range around 55 ppb in the period 2000-2007, while the average value becomes 51 ppb during the period 2008-2010. In figure 2 the average ozone levels and the number of the exceedance days for the treatment and control group over the period 2000-2010 are reported. More specifically, the black and grey lines represent the average ozone levels in the treatment and control group respectively. The black and grey dots represent the number of the exceedance days for the treatment and control group respectively. It is observed, that during the period 2000-2005, without the implementation of the "Clean Air "Works project the ozone levels are similar in both groups. Also the number of exceedance days is similar between the two groups. On the other hand, during the periods 2006-2010, with the implementation of the "Clean Air "Works project, there is an increase in the gap, regarding the average ozone levels and the exceedance days, which are lower in the treatment group. Generally, the graph also indicates that there was a reduction in the average ozone levels and in the number of the exceedance days during period 2008-2010.

6. Empirical results

In this section the quadruple DDDD estimates are presented. The purpose of applying the quadruple DDDD is to examine the effects of the "Clean Air Works" Project on ozone levels, to explore whether or not smog alerts are significant under the program regime and to establish the effects of the change in threshold by EPA from 80 ppb to 75 ppb.

In table 5 the DDDD estimates are reported. Based on these the ozone concentration levels are higher in the treatment group over the period 2000-2010. The average pollution in treatment group is 1.121 ppb higher than in the control group and it is statistically significant. Therefore, the average ozone level in treatment and control group is 53.00 (standard deviation: 16.559) and 51.88 (standard deviation: 15.552) ppb respectively. After the implementation of the program the average ozone level has been reduced by 2.445 ppb in both groups. The interaction term *treat*program,* which is the DD estimator, is negative, significant and equal at -1.268. This indicates that the difference of the average ozone between the treatment and control group, has been reduced after the implementation of the Clean Air Works" program by 1.268 ppb. More specifically, the average ozone level in the treatment and control group before the "Clean Air Works" implementation was respectively 54.344 ppb (standard deviation: 17.244) and 52.250 ppb (standard deviation: 16.627). After the implementation of the program the average ozone levels were 51.936 (standard deviation: 14.476) and 51.110 (standard deviation: 13.951). Thus, the difference-in-difference –DD estimator- is the difference between 0.826 ppb (51.936-51.110) and 2.094 ppb (54.344-52.250) resulting to the estimate -1.268 (0.826-2.094). Therefore, based on the first main coefficient of interest, the DD estimator, the “Clean Air Works” is effective on improving air quality in the treatment group.

Regarding the 2008-2010 period, after the change in threshold, the average pollution level decreased by 3.352 ppb in both groups. Therefore, the average ozone level in the pre-period 2000-2007 and post-period 2008-2010 is 54.35 (standard deviation: 15.642) and 50.98 (standard deviation: 13.286) ppb respectively. The coefficient of *warning* is positive and equal at 6.15, indicating that the average pollution level in both groups is 50.60 (standard deviation: 14.111) ppb in non-smog alert days, and 56.75 (standard deviation: 18.588) during the smog alert days. The interaction term *treat*warning* shows when a smog alert is issued in the treatment group the ozone levels become lower by 0.855 ppb in comparison with the control group and during the period 2000-2010.

The second main coefficient of interest is the DDD estimator which is expressed by the interaction term *treat*program*warning* and it is equal at -1.833 ppb. This shows that the smog alerts are more effective under the program regarding air quality improvement reducing the difference of ozone levels between the two groups. Thus, the results so far support the effectiveness of the “Clean Air Works” project during the whole period of ozone forecast, while the effects are further increased when smog alerts are associated with the program, based on the DDD estimator.

The next interaction terms are *treat*threshold*, *program*threshold* and *warning*threshold.* The first term shows that the difference of the average ozone levels between the treatment and control group have been reduced by 1.545 ppb after the change of the warning threshold. The term *program*threshold* shows that the average ozone levels have been reduced when the "Clean Air Works" is associated with the change of threshold from 80 ppb to 75 ppb. Finally, after the change of the threshold when a smog alert is issued the average ozone levels are lower by 4.259 ppb. The interaction term *treat*program*threshold* is negative and significant indicating that the ozone levels have been reduced in the treatment group after the implementation of the "Clean Air Works" program and the change of the threshold.

The interaction term *treat*warning*threshold* is negative and significant equal at -2.124. In this case the difference of the ozone levels between the treatment and control group have been reduced after the change of the smog alert threshold at 75 ppb, which took place in 2008, and when a smog alert is issued. More specifically, before the change of the threshold the average ozone levels, considering only the days when a smog alert is issued, are 59.677 ppb (standard deviation: 14.808) and 56.375 ppb (standard deviation: 16.276) in the treatment and control group respectively. The respective values after the change in the threshold become 54.722 ppb (standard deviation: 12.383) and 53.545 ppb (standard deviation: 15.776).

Finally, the DDDD estimator which is expressed by the interaction term *Treat* Program*Warning*Threshold* is negative and significant; equal at -1.493. In that case the air quality has been improved in the treatment group in comparison to control group after the implementation of the "Clean Air Works" project and the change of the threshold and when an ozone warning is issued. The DDDD estimator shows that the differences of the ozone levels between the two groups are reduced with the implementation of the program, the change of the threshold and when a smog alert is issued.

Next the robustness checks, discussed in the methodology part, are presented. In table 6 and panel A the robustness check using placebo dummies before the treatment are reported. It becomes clear that the parallel trend assumption is accepted because the DD estimator in panel A of table 6 expressed by the interaction term *treat*program,* is statistically insignificant. This indicates that in the absence of the "Clean Air Works" program the treatment and control group would have the same average trend in ozone levels.

In panel B of table 6 the estimates of regression (3) are reported. More specifically, three estimates are presented, including lags and leads of order 1, 2 and 3. In all cases the leads of $D_{i,j,k,t}$ are statistically insignificant supporting the robustness of our DID estimates. On the other hand, when the treatment is entered with lags is significant in all cases. In conclusions, the results show that the leads are insignificant indicating no evidence for anticipatory effects. Thus, the common trends assumption is accepted. On the contrary, the lags are significant and they show that the effect decreases the ozone levels during the first years of the treatment and the impact on ozone reduction remains significant in the years followed and it is slightly increased at -1.42 ppb. This small increase can be due the fact that the number of "Clean Air Works" program partners has been increased during the period 2006-2010, from 90 to 120.

In figure 3 the DID estimates for the "Clean Air Works" program are presented. More specifically, the black line represents the treatment group without treatment (untreated), while the grey line represents the control group. The black dot-line represents the treatment group after the implementation of the program. The period is expressed in 3 different time lines. The first indicates the beginning of the sample used in this study which is 2000, while the second period indicates the period where the "Clean Air Works" program has been established on 1st March of 2006. Finally, period

3 indicates the establishment of the change of the ozone warning threshold, which took place on 27th May of 2008.

It becomes obvious that the trend before the treatment on the average ozone levels is the same between control and treatment groups. After the implementation of the "Clean Air Works" program the average ozone levels are reduced in a higher rate in the treated group than in the control group. Therefore, based on the robustness checks the common trend assumption is not violated indicating that the deviation of the trend of the observed outcomes (average ozone levels) of the treated from the trend of the observed outcomes of the control (untreated) group are directly attributed to the effect of the treatment as it is shown in the figure 3.

With the DDDD it is possible to examine different cases and differences between control and treatment group. One concluding remark of this study the "Clean Air Works" is effective on improving the air quality in the treatment group. Secondly, smog alerts have additionally significant effects on ozone reduction, when they are associated with the program examined in this study. Thirdly, the quadruple DDDD results show that reducing the threshold from 80 ppb to 75 ppb, a reduction in ozone levels is observed for both treatment and control groups. Moreover, the change of the threshold provides an additional reduction in ozone emission levels, when it is associated with a voluntary program, like "Clean Air Works".

Based on the previous estimates a rough estimate of the number of lives saved from the air quality improvement, under the "Clean Air Works project" associated with the change of the threshold and ozone smog alerts, is presented. Currie and Neidell (2005) find that a one-unit decrease in carbon monoxide (CO) saves 16.5 infant lives per 100,000 births and over 1,000 infants lives are saved from the air pollution reduction during the period 1989-2000, while Knittel et al. (2011) find that it saves 17 lives. Chay and Greenstone (2003a; 2003b) results suggest between 7-15 and 13-23 less deaths per unit decrease of PM_{10}. The literature gives little guidance about when in pregnancy pollution is likely to be most harmful. Currie and Neidell (2005) used pollution measured in the first month of pregnancy, the last trimester of pregnancy and the first trimester of pregnancy. However, because these data are unavailable in this study and the exact time of pregnancy is unknown, pollution measured in trimester basis with one lag (Currie and Neidell, 2005). They find that when the last trimester is used rather than the last month of pregnancy, the air pollution effects are stronger. Similarly, the same interval is taken for the total death and the death rates for elder people.

The death statistics data from the North Carolina State Center of Health statistics are used. The total population during the period 2006-2010 in the treatment group was 1,366,373. Thus, regarding the total deaths, and based on the estimates of table 8 the lives saved by the clean air work program, over the period, are around 425. Respiratory diseases include asthma, bronchitis and pneumonia among others and it is well known that deaths resulted by those diseases are caused by air pollution.

Regarding the effects on infant lives and based on the number of births which was 98,591 during period 2006-2010 it is found that around 211 infant lives have been saved. Finally, the elder population was 33,133. Based on the estimates 38 lives are saved. The remaining deaths belong to the other age groups, including children, but also individuals who suffer from respiratory diseases, which is not possible to identify them based on the available data. Therefore, these estimates are not precise and they could be improved by considering daily and detailed hospitalization, episode statistics and death rates data including gender, race, education level, individual's habits like smoking and alcohol consumption, individual's zip code location and the distance between an air monitor, age and medical background history among others. In addition, as Currie and

Neidell (2005) point out in their study and in other studies too, in this case examined as well, outdoor air quality is measured using a fixed monitor. Actual personal exposures are affected by the time the individual spends indoors and outdoors. Therefore one might expect, for example, that infants spend little time outdoors, so that outdoor air quality might not be relevant.

7. Conclusions

This paper examined the effects of the "Clear Air Works" program implementation on the ozone concentration levels in Charlotte Area in North Carolina State. Moreover, using a DDDD model the effects of the smog alerts under this program additionally associated with the change of the ozone warning threshold from 80 ppb to 75 ppb have been examined.

Based on the estimates, the difference in ozone levels between the treatment and control group has been reduced after the establishment of the "Clear Air Works" program and the smog alerts have an additional effect under this program. The results are consistent with the study by Cutter and Neidell (2009). More specifically the fact that individuals respond to STAs suggests that such voluntary information programs have a potential role in regulatory policy, but such programs alone do not appear to be enough for detecting improvements in air quality; additional incentives appear necessary. Thus, the implication of this program is that additional incentives are required, besides the smog ozone days, in order to improve air quality, such as teleworking, carpool, vanpool, bicycling, public transit and others.

The advisory ozone programs warn the public about forecasted high ozone days, and ask for voluntary actions to reduce emissions of ozone forming pollutants. However, the additional incentives provided by the "Clear Air Works" program are apparently more efficient. Therefore, other areas in North Carolina and other states in USA can implement and follow the example and practices of the specific program. Incentives can include carpool and vanpool programs sponsored by the local governments. Other practices can include incentives to the employers. More specifically, employers can get a tax deduction by giving their employees up to $130 per month to commute via public transit or vanpool. Another incentive is the encouragement of teleworking practices. In this case the employees can save money and time and be less stressful by working at home and at the same time the air quality, through the traffic reduction, can be further improved.

Furthermore, the effects of the air quality improvement, through the program implementation, on mortality have been presented. Concluding, as policy makers discuss ways to improve air quality, the adoption of voluntary programs, such as the "Clean Air Works" program, might be potentially an efficient mechanism. Ultimately, as the results showed about the effects of air quality on mortality, achieving attainment for ozone -air quality better than the national standard- will result in a healthier environment for the region's citizens and work force, and make it more attractive for economic development.

There is one major potential limitation of the analysis. The individual behaviour on transportation mode choice is not examined. Especially, in the case of "Clean Air Works" project, where carpool and vanpool programs, as well as public transit is encouraged and other policies are proposed, the traffic volume is not explored. As it was mentioned, the purpose of this study is the investigation of the effectiveness of the "Clean Air Works" Project the direct examination of ozone forecasts and smog alerts to actual ozone concentrations and their association with "Clean Air Works". Additionally, other studies have already examined the effects of ozone warnings on traffic volume and public health (Cutter and Neidell, 2009; Moretti and Neidell, 2011).

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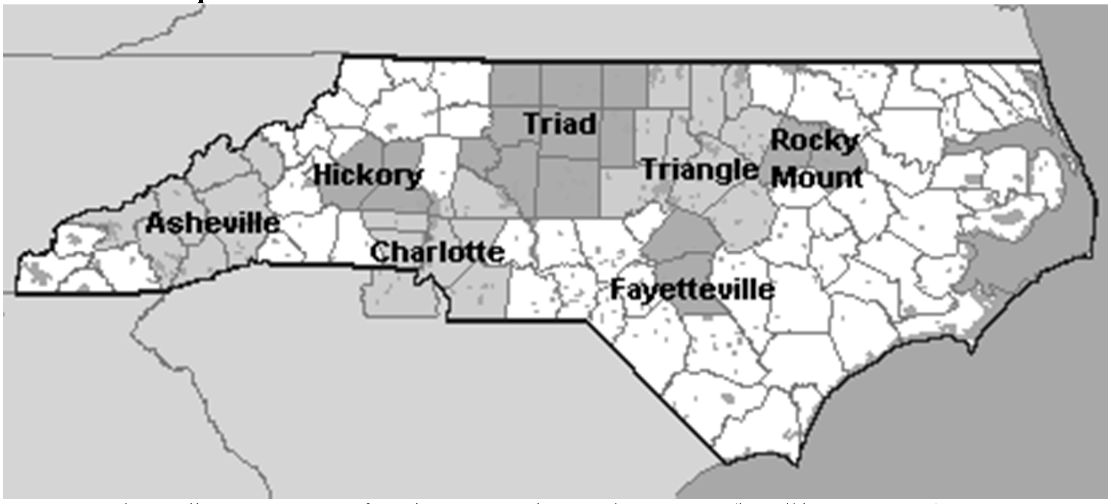
Map 1. Ground-Level Ozone Forecast Zones-Areas in North Carolina



Source: North Carolina Department of Environment and Natural Resources (http://daq.state.nc.us).

Table 1. Treatment and Control Group

Treated Counties	Control Counties
Lincoln (Charlotte area)	Forsyth (Triad area)
Mecklenburg (Charlotte area)	Rockingham (Triad area)
Rowan (Charlotte area)	Guilford (Triad area)
Union (Charlotte area)	Raleigh (Triangle area)
	Cumberland (Fayetteville area)
	Buncombe (Asheville area)
	Caldwell (Hickory area)

Table 2. Date of the events

Date of the Event	Event
1st July 1997	Ozone warning threshold at 80 ppb
1st March 2006	Introduction and Establishment of the "Clean Air Works" program
27th May 2008	Change of ozone warning threshold from 80 ppb at 75 ppb

Table 3. Summary Statistics for Actual Ozone Concentrations expressed in Parts Per Billion (ppb)

	No. observations	Mean	Standard Deviation	Min	Max
Period 2000-2010					
Ground Level Ozone	70,457	51.573	15.160	0	128
Period 2000-2007					
Ground Level Ozone	46,634	53.118	15.642	2	128
Period 2008-2010					
Ground Level Ozone	23,823	49.269	13.285	0	101
Treatment group Period 2000-2010					
Ground Level Ozone	12,684	52.986	16.559	0	128
Treatment group Period 2000-2007					
Ground Level Ozone	8,436	54.272	17.193	2	128
Treatment group Period 2008-2010					
Ground Level Ozone	4,248	51.446	13.314	0	101
Control group Period 2000-2010					
Ground Level Ozone	22,779	51.368	15.552	3	115
Control group Period 2000-2007					
Ground Level Ozone	14,989	52.665	15.768	3	115
Control group Period 2008-2010					
Ground Level Ozone	7,790	50.564	13.538	0	93

Table 4. Exceedance Days of Air Quality Threshold for Ground Level Ozone Concentrations

	Number of exceedance days during period 2000-2005	Number of exceedance days during period 2006-2007	Number of exceedance days during period 2008-2010
Asheville Area	231	20	36
Charlotte Area	683	206	136
Fayeteville	100	11	13
Hickory	44	11	9
Triad	414	87	103
Triangle	425	45	65
Treatment group	648	146	92
Control group	675	198	141

Figure 1. Distribution for Actual Ozone Concentrations Measured in Part Per Billion (ppm) during Period 2000-2010 in Treatment and Control Groups

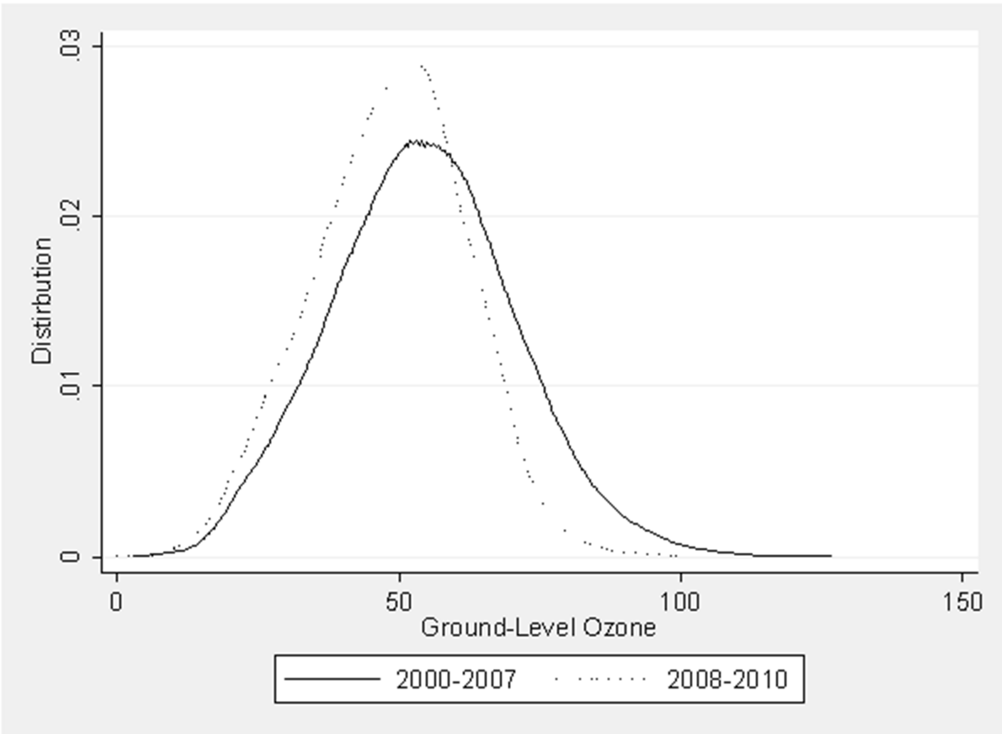


Figure 2. Average Ozone Levels and Number of Exceedance Days in Treatment and Control Group during Period 2000-2010

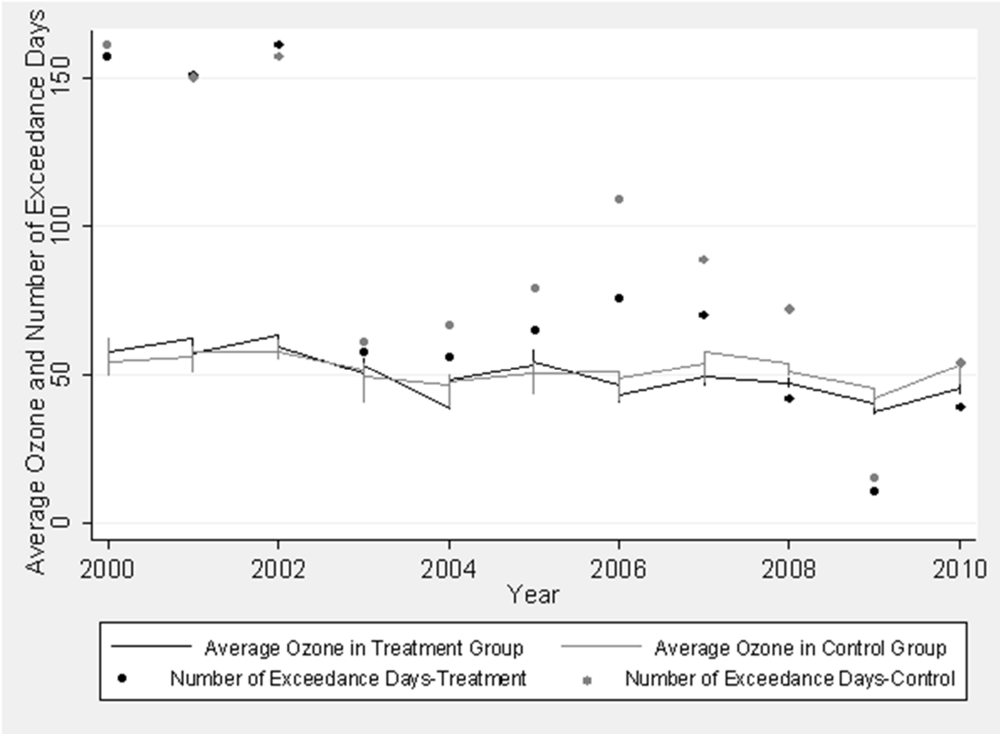


Table 5. Quadruple DDDD Estimates for Equation (1)

Treat	1.121 (0.2274)***	Treat*Program*Warning (DDD effectiveness of smog alerts under Clean Air Works Regime)	-1.833 (0.7553)**
Program (1 for 2006 and after and 0 otherwise	-2.445 (1.2042)**	Treat*Threshold	-1.545 (0.3745)***
Warning (1 for smog alert and 0 otherwise)	6.149 (0.6004)***	Program *Threshold	-1.271 (0.2739)***
Threshold (1 for 2008 and after and 0 otherwise)	-3.352 (0.2808)***	Warning*Threshold	-4.259 (2.235)*
Treat*Program (DD effectiveness of Clean Air Works Program)	-1.268 (0.3887)***	Treat* Program*Threshold	-3.248 (0.3002)***
Treat*Warning	-0.855 (0.4155)**	Treat* Warning*Threshold	-2.124 (0.5153)***
Program* Warning	-1.325 (0.3841)***	Treat* Program*Warning*Threshold (DDDD establishment of the threshold change effect)	-1.493 (0.1131)***
No. obs.	35,463	R^2	0.3790

a. Standard errors are reported between brackets, clustered standard errors at ozone monitoring site
b. ***, ** and * denote significance at the 1%, 5% and 10% level
c. The control variables are: day of the week, month, year, ozone monitoring sites, counties, ozone forecasting regions-areas, average temperature, wind speed, wind direction and solar radiation.

Table 6. Robustness checks for DID regression

	Panel A:Robustness Check Using Placebo Dummies Before the Treatment Regression (2)		
Treat*Program (DD effectiveness of Clean Air Works Program)	0.482 (0.6512)	R^2	0.3347
No. obs.	20,912		

	Panel B:Robustness Check Using Leads and Lags Regression (3)		
$D_{i,j,k,t-1}$	-1.304 (0.621)**	-1.309 (0.628)**	-1.203 (0.623)**
$D_{i,j,k,t-2}$		-1.381 (0.632)**	-1.385 (0.638)**
$D_{i,j,k,t-3}$			-1.422 (0.701)**
$D_{i,j,k,t+1}$	-0.389 (7.671)	-0.373 (8.238)	-0.372 (8..239)
$D_{i,j,k,t+2}$		-0.683 (5.901)	-0.637 (8.337)
$D_{i,j,k,t+3}$			0.525 (5.902)
No. obs.	35,441	35,423	35,402
R^2	0.3426	0.3426	0.3427

a. Standard errors are reported between brackets, clustered standard errors at ozone monitoring site
b. ** denotes significance at the 5% level
c. The dependent variable is the actual ozone levels and the control variables are: day of the week, month, year, ozone monitoring sites, counties, ozone forecasting regions-areas, average temperature, wind speed, wind direction and solar radiation.

Figure 3. DID Estimates for the “Clean Air Works” Program

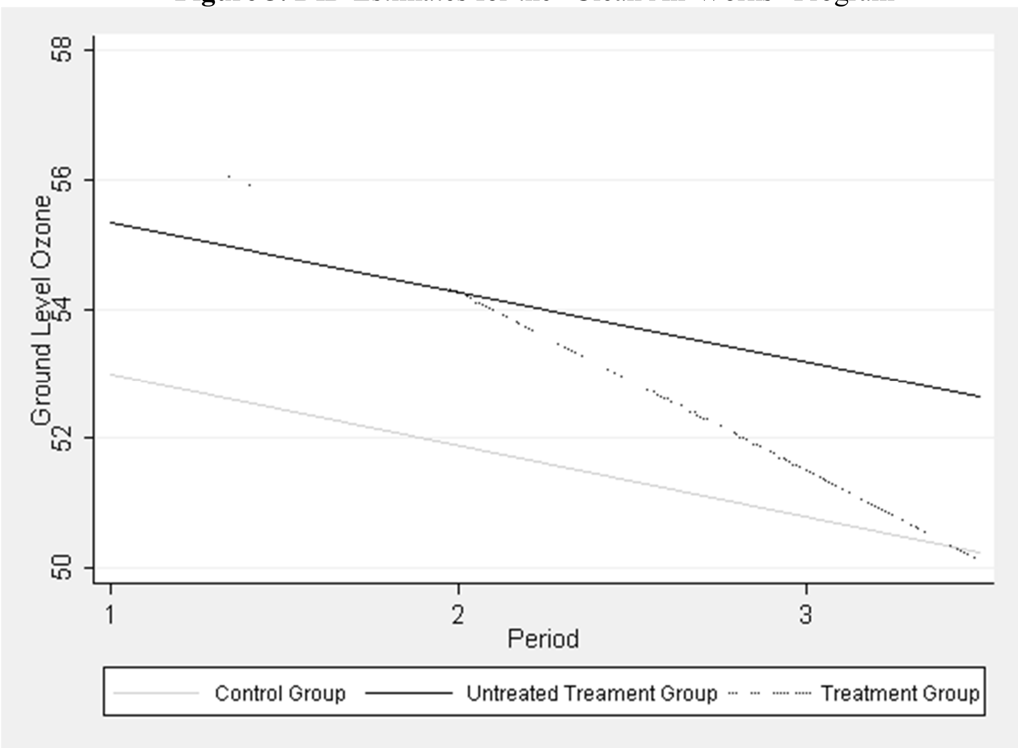


Table 7. Ozone Effects on Deaths Caused by Respiratory and Pneumonia Diseases.

	DV: Respiratory Diseases
Panel A: Total Deaths	
Ozone	0.0156
	(0.0002)***
Obs	60
R squared	0.1586
Panel B: Infant Deaths	
Ozone	0.0885
	(0.0018)***
Obs	60
R squared	0.2284
Panel C: Elder Deaths (60 years and older)	
Ozone	0.0511
	(0.0023)***
Obs	60
R squared	0.0934

a. Standard errors are reported between brackets, clustered standard errors at ozone monitoring site
b. *** denotes significance at the 1% level
c. The dependent variable is the number of deaths caused by respiratory diseases levels and the control variables are: year, ozone monitoring sites, counties, ozone forecasting regions-areas, average temperature, wind speed, wind direction and solar radiation.

Chapter Two

The Effect of Smog-Ozone Warnings and Vanpool Program on Traffic Volume in York County of South Carolina

Eleftherios Giovanis*

Abstract

Ground-level ozone is a critical pollutant that is significantly generated by transportation. Commuting to and from work is a primary cause of increased traffic congestion and air quality problems. Ridesharing programmes, such as carpool and vanpool reduce the number of cars commuting, especially during rush hour, resulting in traffic volume reduction and air quality improvement. The purpose and contribution of the study is the following: Firstly, the study examines the effectiveness of the vanpool programme on traffic volume, which was introduced in 2006 in York County of South Carolina State. Secondly, this study investigates whether the smog alerts are more effective on traffic volume associated with the vanpool programme. Thirdly, the effects of the warning threshold, which was reduced from 80 parts per billion (ppb) to 75 ppb in 2008, are explored. The study period is 2004-2010. A quadruple Differences-in-Differences (DDDD) model is applied. We find that smog alerts and the change in the ozone warning threshold in association with vanpool program lead to significant traffic volume decrease in York County.

Keywords: Air Quality, Differences-in-differences, Ozone concentrations, Regression Discontinuity Design, Smog alerts, Traffic

JEL Codes: I31, Q51, Q53, Q54

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1. Introduction

Voluntary conservation and pecuniary incentives are used in a number of localities across the United States to reduce ozone concentrations, especially on days when air pollution is expected to reach unsafe levels for public health. While air quality has generally improved in recent years throughout the U.S.A., nearly half of all regions that monitor ground-level ozone periodically exceed federal standards for safe ozone concentrations. The goal of this paper is to assess the behavioural responses to ozone warning. More precisely, we estimate whether individuals directly respond to information programs by using vanpool. The vanpooling intends to lower ozone levels and improve the chances of attaining the air quality standards in order to avoid costly regulations. To estimate this relationship between smog alerts and traffic, we use data from York and Spartanburg Counties in South Carolina. Spartanburg and York counties are geographically close, and they share similar demographic and economic characteristics. Both are considered as non-attainment areas by EPA, which means that they do not meet the standards of clean air and have a smog alert system. However, only York County has a sponsored vanpool program. In addition, only two areas are examined, as this allows us for a more appropriate selection of a control and treatment groups, as it is discussed in the data section.

The majority of the studies have examined the effects of ozone forecasts or ozone action days on traffic volume; however the impact of vanpool programs related to ozone forecasts has not been explored yet. The purpose of this paper is to evaluate the smog warnings' effects on traffic volume through ride-sharing and specifically the vanpool program. A smog alert is announced by the responsible state government agency and disseminated through media and other information channels when a high level of ozone pollution is forecasted for the following day. The two main purposes of the ozone warnings are to inform people with respiratory problems to avoid strenuous outdoor activities and to advise individuals and organizations to curb activities that produce ozone precursors. Public advisories typically promote automobile trip reduction and increased public transportation or encouraging alternative modes of transportation, like vanpooling, as primary means by which commuters can reduce pollution. The effect is identified from days with and without smog warning, where the counterfactual being provided by area that does not have a vanpool program in place. During the period 2004-2007 the threshold for warning issue was 80 ppb and this threshold was reduced to 75 ppb during the period 2008-2010.

Commuting to work increases traffic congestion and air quality problems. Reducing the number of cars commuting during rush hours traffic and air pollution can be reduced. Best Workplaces for Commuters in various regions, such as Sacramento in California and Triangle in North Carolina, is a voluntary partnership program designed to cut traffic congestion and traffic-related air pollution. According to Margo Oge, Environmental Protection Agency (EPA) director of the Office of Transportation and Air Quality, the effects of incentive programs like Best Workplaces for Commuters can be dramatic. “If just half of all U.S. employees were covered under these commuter benefits, traffic and air pollution could be cut by the equivalent of taking 15 million cars off the road every year, saving American workers about $12 billion in fuel costs” (http://investor.ecolab.com).

Charlotte Area Transit System (CATS), which straddle North and South Carolina, sponsors a vanpool program. CATS operates 79 active vanpools for commuters seven days a week. The aim of a vanpool program is to allow commuters to ride together in a van, particularly in areas where public transportation is not provided. One rider is the designated driver, and CATS covers the cost of insurance, fuel, maintenance, and a

Guaranteed Ride Home program. The vanpool program currently offers minivans, for four to seven passengers, and vans, for up to 15 passengers at a cost. More precisely, the cost of commuting is shared with the other members of the vanpool. The fare depends on van type and the round trips miles per day.

The Differences-in-Differences (DID) approach is followed, including a control and a treatment group, in order to examine the effects of vanpool program on traffic volume. The DID design evaluates the impact of a program by looking at whether the treatment group deviates from its *baseline mean* by a greater amount than the comparison (control) group. In addition, the difference-in-differences method removes any biases in the second period comparisons between the treatment and control group that could be the result of permanent differences between those groups.

More specifically, a quadruple (DID) framework is applied in order to examine the effectiveness of the vanpool programme on traffic volume between the York County, where the vanpool program exists, and Spartanburg County in North Carolina, where it does not. Secondly, DDD is applied in order to examine whether the smog alerts are more effective under the vanpool programme. Finally, the effects of the change in the warning threshold on traffic volume are established by the DDDD estimator.

The results show that the traffic volume in the York County has been reduced after the implementation of the vanpool program and the difference between the treated and untreated county has been reduced by 700-800 vehicles. In addition, the results show that the smog alerts effectively reduce traffic volume under the vanpool program regime. Finally, when the smog alerts are associated with the vanpool program and the change in threshold from 80 ppb to 75 ppb, which took place in 2008, the difference of the traffic volume between the two Counties has been reduced by 60-70 vehicles. Furthermore, the reduction is stronger during the weekdays and when only the peak hours of the day are considered. This can be explained by the fact that vanpool program mainly targets employees.

The robustness checks confirm the validity of the DID results. More specifically the treatment and control group used in the DID design must have similar pre-intervention outcomes and characteristics. This is known as the "Parallel" or "Common" trend assumption, which posits that the average change in the comparison group represents the counterfactual change in the treatment group if there were no treatment. Based on the sensitivity analysis the null hypothesis of equal trends between treatment and controls, before the implementation of the vanpool program, is accepted.

The structure of the paper is as follows: In section 2 the literature review is provided. Section 3 reviews the methodology of the DDDD model used in this study. Section 4 presents the data, and the research sample used in the estimations, while in section 5 the empirical findings are reported. In the last section the general conclusions of the empirical findings are presented.

2. Literature Review

2.1 Air pollution and public health

This section discusses the previous literature on the relationship between air pollution and health which will confirm our results about the effects of smog alerts and vanpool programme on traffic volume reduction and infant mortality. Moreover, weather conditions, economic recessions and the type of the ventilation filter on vehicles and theirs effects on air pollution and health have been explored. However, the contribution of this study is that controlling for recession periods and weather conditions, the effects of vanpool programme and smog alerts on traffic volume are examined. In addition, the effects of the air pollution reduction through the decrease of traffic volume, caused by the vanpool programme and smog alerts, on infant mortality are explored.

The association between mortality rate and particulate air pollution has long been studied. Dockery et al. (1993) related excess daily mortality from cancer and cardiopulmonary disease to several air pollutants, especially fine particulate matter $PM_{2.5}$. Since then, many other epidemiological studies on the adverse effects of air pollutants have been carried out, ranging from variations in physiological functions and subclinical symptoms like heart rate variability and peaκ respiratory flow rate, to manifest clinical diseases such as asthma, stroke, lung cancer, and leukaemia, premature births and deaths (Delfino et al., 1998; Naeher et al., 1999; Laden et al., 2000; Suresh et al., 2000; Janssen et al., 2002; Wilhelm and Ritz, 2003; O'Neill et al., 2004; Preutthipan et al., 2004). More specifically, Delfino et al., (1998) report that the emergency rooms usages were 21.8 per cent higher than average for a mean increase of 44 O_3 parts per billion (ppb), while an increase in $PM_{2.5}$ from coal combustion sources accounted for a 1.1% increase in daily mortality (Laden et al., 2000).

Next the results of the study conducted by Currie and Neidell (2005) are presented. Their estimates will be used for our back-off-envelope calculations of the air pollution reduction on infant mortality, caused by the traffic reduction as a result of vanpool program and smog alerts. Currie and Neidell (2005) using the California Birth Cohort files and the California Ambient Air Quality Data during period 1989-2000 propose an identification strategy using individual level data and exploiting within-zip code-month variation in pollution levels. Creating measures of pollution at the zip code-week level they control for individual differences between mothers that may be associated with variation in birth outcomes. The authors find little average effect of prenatal pollution exposure on the probability of low birth weight, short gestation and fetal death after including the mother's zip code in the model. However, the authors find that living in a very high-pollution area is associated with a higher risk of fetal death, suggesting that pollution may be harmful above a certain threshold level. Their estimates suggest that the reductions in CO and PM_{10} that occurred saved more than 1,000 infant lives in California during the period 1989-2000 examined. Using their estimates and the results from this study the number of total lives saved are 190.

Currie and Walker (2011) examined the effect of improvements in traffic congestion on infant health. The difficulty in this literature is that individuals willing to live in polluted areas are likely to differ, including their health level, from those living in less polluted areas. As such, Currie and Walker (2011) rely on a natural experiment which exogenously reduced the pollution level in some areas. More specifically engineering studies suggest that the introduction of E-ZPass in the Northeast of the US, sharply reduced delays at toll plazas and pollution caused by idling, decelerating, and accelerating vehicles. Currie and Walker (2011) show that E-ZPass reduced the incidence of prematurity and low birth weight in the vicinity of toll plazas by 6.7-9.1 percent and 8.5-11.3 percent respectively. This study follows a similar approach to Currie and Walker’s (2011) study, who employed a DID modelling to examine the effects of the E-ZPass policy before and after its implementation. However, this study differs and adds to the existing literature by applying a quadruple DID model and estimating the effectiveness of the vanpool program in York County and whether the smog alerts are more effective when these are associated with the change in the warning threshold.

Next two related studies to our analysis by Chay and Greenstone (2003a; 2003b) are discussed. More specifically, these studies consider the effects of air pollution variation, caused by economic recession and expansion periods, on infant mortality. This is related to our study because we consider also the pre-recession period 2004-2007 and the recession period started in the beginning of 2008. Chay and Greenstone (2003a) examined the air quality improvements induced by the Clean Air Act Amendments (CAAAs) of 1970 to estimate the impact of particulates pollution on infant mortality during the period 1971-1972. Their strategy has some attractive features, since federally-mandated regulatory pressure is orthogonal to county-level changes in infant mortality rates, except through its impact on air pollution and thus can be used as an instrument. Also the authors use regulation-induced changes that occurred during an economic expansion period 1971-1972; thus, any potential biases due to economic shocks are likely to be mitigated. The federal air pollution regulations are associated with sharp reductions in both total suspended particulates (TSPs) pollution and infant mortality rates in the first year that the 1970 Clean Air Act Amendments were in force. The authors find that a one per cent decline in TSP results in a 0.5 per cent decline in the infant mortality rate. Chay and Greenstone (2003b) used substantial differences in air pollution reductions across sites to estimate the impact of TSPs on infant mortality. The authors establish that most of the 1980-82 declining in TSPs was attributable to the differential impacts of the 1981-82 recession across counties. The authors find that a one percent reduction in TSPs results in a 0.35 percent decline in the infant mortality rate at the county level.

Next two studies by Knittel et al. (2011) and Beatty and Shimshack (2011) related to our study are discussed. More specifically, Knittel et al. (2011) considers the effects of weather conditions as this study controls for. Secondly, Beatty and Shimshack (2011) examined the positive effects of crankcase ventilation filter/valve (CCV) retrofits of school buses on air quality. This is the case of our analysis where the type of vans employed in vanpool programme use CCV. In addition, a regular maintenance for best performance and peak fuel efficiency takes place, which includes regular change of the air filter and the CCV. Knittel et al. (2011) examined the effects of PM_{10} in California Central Valley and Southern California in the years 2002-2007. Knittel et al. (2011) used as an instrument to PM_{10} weekly shocks to traffic and its interactions with ambient weather conditions. The authors argue that deviation from the regional norm originates from accidents and road closures. These shocks to traffic, and thus pollution, are likely to be uncorrelated with the error term in a model of infant mortality as a function of pollution exposure. Knittel et al. (2011) find that PM_{10} has a large and statistically significant effect on infant mortality. Beatty and Shimshack (2011) examined the crankcase ventilation filter (CCV) retrofits of school buses on respiratory health, and specifically bronchitis, asthma, and pneumonia. Beatty and Shimshack (2011) use hospital discharge data from the Washington State Department of Health and the retrofit database which consisted of approximately 4,000 buses in 53 school districts of the Puget Sound area of Washington State. Beatty and Shimshack (2011) find that school bus retrofits induced statistically significant and large reductions in bronchitis, asthma and pneumonia incidence for children and adults with chronic conditions.

2.2 The effect of information system on human behaviour change

This section presents and discusses previous studies examining the public information system and human behaviour change. Most research studies examined the ozone advisories programs effects on traffic volume and not the vanpool or carpool programs. Several Air Quality Management Districts (AQMDs) in California have implemented ozone outreach action programs, called “Spare the Air” (STA), to elicit voluntary reductions in ozone-producing activities. STAs are issued when ozone levels are predicted to exceed a particular threshold. Schreffler (2003) focused on “Spare the Air” advisory program by conducting a small telephone survey in the Bay Area that requested daily travel activities, and found a statistically significant 4.8 percent reduction in trips when smog alerts were implemented. This resulted in an emission reduction of 1.04 tons of ozone precursors, or 0.74 tons after controlling for trip reduction on non-Spare the Air days and he estimated that drivers, on average, took 0.45 less trips on STA days or 4.68 tons of ozone precursors.

Cummings and Walker (2000) examined a similar voluntary program in the metropolitan area of Atlanta on hourly traffic volumes and found statistically insignificant effects. More specifically, the authors control for traffic recorders, time effects, as in months, days and holidays, and weather conditions. Lastly whether a day is an action ozone day or not is considered in the analysis. However, theirs estimates show that it has no significant different effects on traffic volume. These studies are similar with the aim of this chapter. However, this study adds and contributes in the existing literature by examining a voluntary program and specifically the effectiveness of vanpool program on traffic.

Welch et al. (2005) examined the impact of ozone advisories on hourly train usein Chicago (Illinois) during the period 2002-2003 controlling for weather conditions, days, months and holidays. The findings suggests that while the overall effect of ozone action days on train use is not significant, there are statistically significant changes in hourly ridership patterns. More specifically, the authors found increases during peak commuting periods and decreases during non-peak hours. Cutter and Neidell (2009) examined the effects of “Spare the Air” advisory program in San Francisco Bay Area using the metropolitan region of Los Angeles as a control group. The authors estimate a regression discontinuity approach using a sample of observations within 2 and 1 ppb of the limit for a STA call and they show a statistically significant drop in vehicle usage of between 2,000 and 2,300.

Lu et al. (2004) collected comprehensive travel data of a random sample of the general population and of individuals who said they responded to the Spare the Air (STA) message during two summer ozone seasons in Sacramento. The authors studied the travel behaviour of the same individuals on both Spare the Air and regular- non-Spare the Air - summer days and of individuals located in STA and non-STA areas. They found a statistically significant difference between self-reported vehicle trip reductions and measured vehicle trip changes due to Spare the Air programs among STA participants.

It should be noticed that the previous studies do not consider the weather conditions. The exception is the study by Welch et al. (2005) who use various weather conditions including temperature, rainy days and extreme weather conditions, while the study by Cutter and Neidell (2009) employs only temperature and solar radiation. This study adds to the literature by examining the vanpool program and considering for weather conditions, such as temperature, humidity, precipitation and wind speed. Weather is important because it can influence the traffic pattern and flow. For example Roh et al. (2013) found a positive association between traffic volume and sunny days. Welch et al. (2005) found that high temperature days are positively associated with public transit ridership, while bad weather and holidays tend to reduce the number of people taking public transportation. The studies by Knapp and Smithson, (2000) and by Datla and Sharma (2010) show that extreme weather conditions cause travel disruptions and delays. Moreover, previous researches ignore the day of the week effects. Welch et al. (2005) found that more people take the train on Monday than on Friday. However, the studies by Roh et al. (2013), Knapp and Smithson, (2000) and Datla and Sharma (2010) do not examine the vanpool program and the change in warning threshold.

This part introduced us to the previous research examining the effects of public information system on human behaviour and the association between air pollution and health. This study contributes to the previous literature by examining the effectiveness of vanpool program and the ozone advisory systems and smog alerts on traffic volume. Thus in summary, prior empirical and theoretical research provides sufficient means to link the ozone public information advisories to changes in travel behaviour. In addition, the previous research suggests that there are still significant opportunities to improve the ability of public advisories to elicit changes in citizen travel behaviour. Moreover, it is possible that some citizens are persuaded, due to health or environmental predispositions, or encouraged, through sponsored voluntary programs- such as the vanpool program examined in this chapter- to alter their travel behaviour in ozone action days. Finally, this study controls for temperature and humidity, as well as, for extreme weather conditions captured by minimum and maximum temperature and wind speed.

3. Data

The data for forecasting ozone concentrations have been retrieved from the South Carolina Department of Health and Environmental Control (http://www.scdhec.gov). Traffic volume data comes directly from the Traffic Polling and Analysis System of South Carolina (http://www.scdot.org). The weather and meteorological data have been found onTuTiempo.net, which contains a detailed database for all monitoring stations in South Carolina. The period used in the study is 2004-2010. Table 1 presents the scale developed by Environmental Protection Agency that relates shorter and longer-term exposure to the ambient ozone concentrations, in parts per billion (ppb), to health risk.

The air quality forecasts are provided as part of the air quality index by EPA, which sets the National Ambient Air Quality Standards (NAAQS). This index ranges from 0 to 500. The purpose of the Air Quality Index (AQI) is to help people understand what local air quality means to their health. To make it easier to understand, the Air Quality Index is divided into six levels of health concern: and addresses the ranges of ozone that are represented by the AQI categories, such as "good," "moderate," "unhealthy for sensitive groups," "unhealthy", "very unhealthy" and "hazardous" based on table 1 (Environmental Protection Agency, 2008). An Air Quality Index value of 100 generally corresponds to the national air quality standard for the pollutant. Air Quality Index values below 100 are generally thought of as satisfactory. When Air Quality Index values are above 100, air quality is considered to be unhealthy-at first for certain sensitive groups of people, then for everyone as Air Quality Index values get higher. Since 1997 the national standard was set up at 80 particles per billion (ppb). This standard was reduced to 75 ppb in 2008. Under the revised AQI, ozone levels above 75 ppb would be classified as "unhealthy for sensitive groups"–known to many people as a "code orange" air quality day. When ozone is in this category, EPA recommends certain groups to adjust their activity levels to reduce their ozone exposure. These groups include children and adults who are active outdoors, people with asthma or other lung diseases and older adults. As it is shown in table 1, from 2008 onwards, an ozone value of 75 particles per billion (ppb) or 0.075 ppm corresponds at the value of 100 for Air Quality Index. More details about what each Air Quality Index scale means are reported in table 1. In addition, Air Quality Index is calculated based on a specific formula and the ozone concentrations.[2]

Figures 1-2 present the Kernel density distribution of the daily traffic volume in York and Spartanburg County respectively for the full period 2004-2010, as well as for the sub-periods 2004-2005 (before the vanpool program implementation), 2006-2007 (after the implementation of the program) and 2008-2010 (after the change in warning threshold). The black line represents the period 2004-2010, the grey line represents the period 2004-2005, the black long-dash dot line expresses the period 2006-2007, while the tight dot line represents the period 2008-2010. During the period 2004-2010 the average value of traffic volume for York and Spartanburg County are 36,824 and 36,764 respectively. The respective values for period 2004-2005 are 37,102 and 36,300 for York and Spartanburg County respectively, while during the period 2006-2007 the average traffic volume was 37,300 and 37,200 for York and Spartanburg County respectively. Thus, the average traffic volume has significantly decreased in York County after the implementation of the vanpool program. During the period 2008-2010 after the change in warning threshold the average traffic volume in York County reduced at 37,585, while in Spartanburg County has been increased at 37,251. However, based on figures 1-2 it seems that there is no difference in traffic volume patterns for more than 50,000. This can be explained by the fact that volumes for more than 50,000 are referred mainly in the peak hours where individuals travel especially for job reasons. Nevertheless, the results show that the differences are small, but the difference in the traffic volume between treatment and control County has been reduced by around 700-8000 vehicles, after the implementation of the vanpool program, which it is not clear on

[2]The AQI conversion formula is defined as:
$AQI=\frac{I_{HI}-I_{LO}}{BP_{HI}-BP_{LO}}\cdot(C_{03}-BP_{LO})+I_{LO}$, where AQI is the air quality index, I_{LO} and I_{HI} are the index values at the lower and upper limit respectively of the AQI category, BP_{LO} and BP_{HI} are the break-point concentrations at lower and upper limit respectively of AQI category and C_{03} is the ozone concentration level.

the figures. On the other hand, there are differences in the traffic patterns for volumes less than 50,000. This can be explained by the fact that these volumes capture the off-peak hours, as well as the weekends. This shows that individuals in York County motivated by the vanpool program might use less private cars that the individuals in Spartanburg County.

The regressions are based on daily data. The data split is the following. For the total sample the sum of the hourly data of each day is calculated. However, for the sample including only the peak hours the sum of the peak hours during a day is considered, which is between 6:00-10:00 a.m. and 16:00-19:00 p.m. (Cutter and Neidell, 2009). In addition, the regressions control for the day of the week, the month and the year.

Next some demographic and economic descriptive statistics are reported in order to assess whether the treatment and control groups are equivalent. The tables 2-5 display descriptive statistics for the treatment and control groups; York and Spartanburg County, and specifically, age groups, racial groups, number of firms and employees and major industries, unemployment rate, mean household income and its distribution.

Mean values of these variables were obtained for treatment and control groups and a standard statistical test of the difference between these mean values. In table 2 the age groups in thousands and proportions of the total population are presented. Based on *t-statistic* the null hypothesis of equality of the means between the two Counties is accepted in all cases except for the age group of 65 year old and over, where the null hypothesis is rejected at 5 per cent significance level.

In table 3 the number and the proportion for racial background is reported. It becomes clear that the differences between the two counties are insignificant. However, regarding the Asians, based on *t-statistic* and the *p-value* the null hypothesis, that the two samples are equal, is rejected at 10% level. In table 4 the number of the firms and employees and major industries are reported. The results show that there are not significant differences between the two Counties; however, the number of employees in the *Finance and Insurance* industry are significant higher in York County. On the other hand, the *Wholesale and Retail Trade* presents a significant higher number of employees in Spartanburg County than in York. Therefore, it is important to control in the regressions for demographic and industry characteristics.

In table 5 the unemployment rate and the per capita income are reported. It is observed that the unemployment rate between York and Spartanburg County was similar during the period 2006-2010. Based on the *t-statistic*, the null hypothesis that the unemployment rate in two counties is equal is accepted with a *p-value* equal at 0.5811. Similarly, the per capita income is similar between the two counties. Based on table 5 and the*t-statistic* the mean income between the two counties is equal and the *p-value* is found to be 0.2112.

It becomes apparent that the choice of Spartanburg County as control is indeed successful as any differences between the two groups are not statistically significant. However, there are significant differences between the two Counties regarding the industrial sectors *Finance and Insurance* and *Wholesale* and *Retail Trade*; thus the demographic and industry characteristics reported in table 2-5 are included as additional controls in the regressions.

4. Econometric Framework

Individuals have three main choices, to drive alone, to use public transport and to not take a trip. Additionally, vanpooling is an option in York County, as there is a sponsored vanpool program from Charlotte Area Transit System, which is supported by the Environmental Protection Agency.

EPA and CATS in collaboration with companies encourage employees to reduce the number of vehicles on the road and use vanpooling as an alternative transportation option. More specifically, CATS provides and promotes vanpooling as an alternative way of commuting to the citizens who live and work in York County. Activities undertaken include promotion and expansion of the vanpool program and increasing its use. In addition, the CATS advertises and utilises the Web-based rideshare vanpool matching program ShareTheRideNC.org. During 2006, it is estimated that the vanpool program provided approximately 98,550 passenger trips which averaged 89 miles per day, saving more than 8.7 million vehicle miles of travel (South Carolina Department of Transportation, Public Transportation Division, http://www.scdot.org/).

The reason why Spartanburg County is taken as the control group is that it shares similar air quality with York County and geographically both counties are very close, as map 1 shows. In addition Spartanburg County has a smog alert system, but not a vanpool program. Moreover, both counties are considered as non-attainment areas by EPA, which means that they do not meet the standards of clean air. Finally, both countries share similar economic and demographic characteristics as it has been described in the previous section.

(Enter Map 1)

Also the current vanpool program in York County mainly targets employees, therefore it is expected the effects of the warning issues on vanpooling to be stronger during the weekday peak hours. The use of DID in that case is very useful for the following reasons: The simplest set up is one where outcomes are observed for two groups for two time periods. One of the groups is exposed to a treatment-which is the vanpool program in York county- while the second group-control- is not exposed to the treatment during either period, while in both groups a smog alert system is available. In the case where the same units within a group are observed in each time period, the average gain in the second (control) group is subtracted from the average gain in the first (treatment) group. This removes biases in second period comparisons between the treatment and control group that could be the result from permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of trends. The quadruple DID is:

$$\begin{aligned}
& traffic_{i,j,t} = \beta_1 treat_{i,j,t} + \beta_2 vanpool_program_{i,j,t} + \beta_3 warning_{i,j,t} + \beta_4 threshold_{i,j,t} + \\
& \beta_5 treat_{i,j,t} * vanpool_program_{i,j,t} + \beta_6 treat_{i,j,t} * warning_{i,j,t} + \beta_7 treat_{i,j,t} * threshold_{i,j,t} + \\
& \beta_8 vanpool_program_{i,j,t} * warning_{i,j,t} + \beta_9 vanpool_program_{i,j,t} * threshold_{i,j,t} + \\
& \beta_{10} warning_{i,j,t} * threshold_{i,j,t} + \beta_{11} treat_{i,j,t} * vanpool_program_{i,j,t} * warning_{i,j,t} + \\
& \beta_{12} treat_{i,j,t} * vanpool_program_{i,j,t} * threshold_{i,j,t} + \\
& \beta_{13} vanpool_program_{i,j,t} * warning_{i,j,t} * threshold_{i,j,t} + \\
& \beta_{14} treat_{i,j,t} * vanpool_program_{i,j,t} * warning_{i,j,t} * threshold_{i,j,t} + W_{i,j,t} + \mu_i + l_j + \theta_t + \varepsilon_{i,j,t}
\end{aligned} \tag{1}$$

Variable *traffic* is the traffic volume, subscript i represents the traffic monitoring site, subscript j denotes the ozone monitoring site and subscript t indicates time. *Treat* denotes the treatment group, which in this case takes value 1 for York County and 0 otherwise. *Vanpool_program* takes value 1 since the sponsored vanpool program started its implementation in 1st January of 2006 and afterwards and 0 otherwise. *Warning* indicates the ozone warnings and it is a dummy variable taking value 1 whether there is a smog alert and 0 otherwise, while *threshold* denotes the change of smog alert threshold from 80 ppb to 75 ppb and takes value 1 for 27th May of 2008 and afterwards and 0 otherwise. Vector W includes meteorological variables as minimum, maximum and average temperature, humidity, precipitation and wind speed, which have been ignored in previous studies (Schreffler, 2003; Cutter and Neidell, 2009). Set μ_i includes traffic monitoring dummy variables, l_j controls for counties, while θ_t controls for the day of the week, the month and the year. Finally, traffic monitoring sites are clustered in order to take robust standard errors.

The interaction term *treat*vanpool_program* is the diff-in-diff (DD) estimator which show the effectiveness of the vanpool program on traffic reduction, while the interaction term, *treat*vanpool_program*warning* is the triple DDD estimator which shows whether the smog alerts are more effective when they are associated with the vanpool program. Finally, the interaction term *treat*vanpool_program*warning*thres-hold* is the quadruple DDDD estimator which examines the effectiveness, on traffic volume, of the smog alert threshold change in 2008 at 75 ppb.

To account for any transitory shocks specific to a monitoring station, such as a highway construction project that could affect traffic for several consecutive days, we estimate the model with a lagged dependent variable, following the Arellano-Bond GMM (1991). This strategy is followed also by Cummings and Walker (2000) and Welch et al. (2005), who include traffic or public transit lags from the previous hour, which in effect is comparing whether transportation choices changed within a day. GMM is preferred over dynamic FE model for the reason that the lagged dependent variable in the FE model gives rise to autocorrelation (Nickell 1981). In addition, time-invariant fixed effects air monitor, traffic sites and county characteristics may be correlated with the explanatory variables. Regarding 2SLS, GMM is preferred because the former is inefficient in the general over-identified cases with heteroskedasticity and when there is serial correlation in the error terms. However, if the error term is homoskedastic and it is non-autocorrelated, then there is no reason to use GMM instead of 2SLS. Nevertheless, if there is heteroskedasticity or serial correlation in error terms, as it can be the case examined in this study, the 2SLS estimator will be no longer asymptotically efficient, but it will remain consistent. In that case the two most common ways of guarding against heteroskedasticity is either using a heteroskedasticity-robust estimator of the variance matrix or using GMM estimator (Wooldridge, 2010).

Therefore using the DDDD it becomes feasible to examine various effects. However, the key identification assumption of DID is that the two groups experience the same changes over time, on average. In other words, there is a common trend in the absence of the treatment and this assumption is known as “Common” or “Parallel” Trend. In particular, it is assumed that in the absence of the vanpool program, the trends in traffic volume between the treatment and control Counties would have been the same, and that no other factors that might affect the traffic volume, occurred at the same time as the vanpool program. If this assumption is violated, then the DD estimates will be biased. “Placebo” dummies before the implementation of the vanpool program are assigned in order to formally test this assumption. In addition, leads and lags are introduced to the basic DID model to examine the dynamics of the program and to test whether the leads and lags of the treatment are significant or not.

5. Empirical Results and Discussions

In this section the DDDD estimates are presented. The aim of using quadruple DID is threefold. Firstly, the effectiveness of the vanpool program is examined. Thus, using a treated and untreated group the difference on traffic volume before and after the implementation of the vanpool program is explored, which is the DD estimator and is represented by coefficient β_5 in model (1) described in the methodology section. Secondly, the purpose of regression (1) is to examine whether the smog alerts are effective when these are associated with the vanpool program and it is captured by the coefficient β_{11} in model (1), which is the DDD estimator. Finally, the establishment of the effects on traffic volume after the change in threshold by EPA from 80 ppb to 75 ppb is examined. This is captured by the coefficient β_{14} in model (1) and it is the DDDD estimator.

In table 6 the quadruple DDDD estimates are reported for four different cases. In panel A and columns (1)-(2) the static fixed effects and GMM estimates respectively are reported for the total hours of the day and all days of the week. In columns (3)-(4) the same estimates are presented, but obtaining only the peak hours of the day. The respective estimates are reported in panel B excluding the weekends. Based on the results reported in panel A, columns (1)-(2) and the total hours of the day, the DD estimator is -800 and -700 respectively for static fixed effects and GMM estimates. This indicates that after the implementation of the vanpool program the difference in traffic volume between the treated County (York) and the untreated (Spartanburg) has been reduced by 700-800 vehicles. More specifically, based on the estimates of table 6 the average traffic volume in treatment and control group was around 36,700 and 35,800 respectively, while after the implementation of the vanpool program the respective average values are around 37,400 and 37,200 for the treatment and control group respectively. Similarly, when the peak hours of the day only are considered then the difference increases at 750-800 based on columns (3)-(4) and panel A.

Regarding the triple DDD estimator the difference in traffic volume between the treated and the untreated County has been reduced by 220-240. The difference becomes 230-300 respectively for the static fixed effects and GMM estimates, when only the peak hours of the day are considered. The DDD estimator shows the effects of the smog alerts after the implementation of the vanpool program. The coefficient of the DDD estimator is significant in all cases indicating that the smog alerts are effective under the program regime in the treated County.

Finally, the DDDD estimator, which establishes the effects of the change in warning threshold from 80 ppb at 75 ppb in 2008 on traffic volume, is negative and significant. More specifically, the traffic volume in the treated county after the implementation of the vanpool program associated with smog alerts and the change in the warning threshold has been reduced relatively to the control County by around 60-80 vehicles.

The same estimates are reported in panel B with the exception that only Mondays-Fridays are included in the regressions. The results are similar with those derived when all the days of the week are obtained. However, when only the peak hours are considered the difference of the traffic volume reduction between the treated and untreated County is higher during the Mondays-Fridays sample relatively to the whole week sample.

The next step is to test the parallel or common trend assumption. In order to do that placebo dummies before the treatment are placed. In that case DID is estimated assuming that the vanpool took place before 2006. Because of the traffic data availability the estimated period is 2004-2010, as it has been described in the data section. For this reason we assume that the vanpool program took place in 2005 instead of 2006 and the basic DD model is estimated during the period 2004-2005:

$$traffic_{i,j,t} = \beta_1 treat_{i,j,t} + \beta_2 vanpool\_program_{i,j,t} + \\ \beta_3 treat_{i,j,t} * vanpool\_program_{i,j,t} + W_{i,j,t} + \mu_i + l_j + \theta_t + \varepsilon_{i,j,t} \tag{2}$$

Next a full set of lags and leads is introduced in the basic DID model (2). Including leads into the DID model is a way to analyse pre-trends, while lags can be included in order to analyse whether the treatment effect changes over time after the implementation of the vanpool program. Regression (2) is written as:

$$traffic_{i,j,t} = \beta_1 treat_{i,j,t} + \beta_2 vanpool\_program_{i,j,t} + + \sum_{p=0}^{m} \beta_{-p} D_{i,j,k,t-p} + \sum_{p=1}^{q} \beta_{-p} D_{i,j,k,t+p} + \\ W_{i,j,t} + \mu_i + l_j + \theta_t + \varepsilon_{i,j,t} \tag{3}$$

As it has been discussed in chapter 1, regression (3) is testing for causality in the framework of Granger (1969) and $D_{i,j,k,t}$ is defined as the interaction term *treat*program* as defined in regression (1). Similarly, with the first chapter, *m* lags define post-treatment effects and *q* leads define the anticipatory effects. If the treatment is causal it is expected that the leads should show no effect of treatment or in other words the leads should be insignificant.

In table 7 and panel A the estimates of regression (2) are presented. In that case, a placebo dummy before the treatment is placed. The DD estimator is insignificant and it is suggests that the common trend assumption holds. In panel B the estimates for regression (3) are reported, including three specifications; with one, two and three lags and leads respectively and considering the total and the peak hours of the day. The leads in all cases are statistically insignificant indicating that there are no anticipatory effects and the common trend assumption is accepted. On the contrary the lags are negative and significant showing the post-treatment effects on traffic volume. In addition, from the figure 3 it becomes clear that the common trend assumption is accepted. Figure 3 shows the difference between what the traffic volume outcome actually is and what it would have been in the absence of treatment which is the DID estimate of the treatment effect. More specifically, the black line shows how the treatment group would have developed in the absence of treatment and under the common trend assumption. The black dot-line represents the treatment group after the implementation of the program, where is represented by the vertical black line in 2006.

The findings are consistent with Cutter and Neidell's (2009) study. The results show that ozone warnings successfully inform people and promote automobile trip reduction by encouraging alternative modes of transportation, like vanpooling, as primary means by which commuters can reduce pollution. In addition, given that ozone concentrations typically peak in the late afternoon during the peak hours, the results show that warnings have a greater impact on traffic reduction during these hours. In addition, we consistently find that the warning system leads to a greater reduction in traffic flow in York County than in Spartanburg County. This can be explained by the fact that York County additionally sponsors and offers a vanpool program. Such a program provides alternatives to own driving which allows more individuals to not drive on alert days.The reduction is strongest during weekdays and peak time, which is consistent with the vanpool assumption; as such scheme targets mainly employees.

We can compute some back of the envelope computation of how much the warning system and its association with vanpooling program reduces pollution. Based on estimates an average car increases ozone levels by 0.00000515 ppm in a day. The DD estimates suggest that the vanpool program leads to a reduction of 800 cars a day leading to a reduction of 0.00412 ppm per day in ozone level. Next we use by Currie and Neidell's (2005) estimates of ozone on infant mortality at face value. Their estimates show that a one-unit increase of ozone levels increases infant mortality by 0.144. Therefore, obtaining this estimate and using the infant mortality rate in York and Spartanburg Counties multiplying by the reduction of the ozone levels, the ozone warning system led to a total reduction in deaths over the period, given 33,571 births, of around 190. However, these calculations suffer from the drawback that this study, like the Cutter and Neidell's (2009) does not examine type of cars. As such those calculations are slightly biased upwards, if the remaining cars are more likely to be vans that are on average more polluting.

6. Conclusions

Previous studies have estimated the responsiveness of motorists to episodic appeals for car trip reductions (Cummings and Walker, 2000; Schreffler, 2003; Lu et al., 2004; Welch et al., 2005; Cutter and Neidell, 2009). However, this is the first analysis examining the effectiveness of the vanpool program implementation on traffic volume reduction. In addition, the study explored whether individuals change their behaviour when a smog warning is issued in York County under the vanpool program. Finally, the effects of the change in the warning threshold on traffic volume have been established. The traffic volume has been significantly reduced in York County relatively to Spartanburg County and the difference on traffic volume reduction ranges between 700-800 vehicles. Moreover, when an ozone warning is issued, the traffic volume is further reduced in York County by 240-280, than in Spartanburg County. Therefore, vanpooling, associated with the smog alerts and the change in threshold, has significant effects on traffic reduction.

These results are explained by the fact that vanpool helps to reduce traffic and makes the most of an area's road infrastructure, leading this way to air pollution reduction. In addition, vanpool also contributes to energy consumption, gas consumption and exhaust emissions reduction and every vehicle left at home helps improve air quality. As policy makers discuss ways to improve air quality, the adoption of voluntary programs, such as the vanpooling, can be a potentially useful mechanism. Moreover it is necessary to determine how these programs can be best incorporated into state and local efforts to meet air quality standards. Overall, various practices can be applied in other areas following the example of the sponsored vanpool program in York County, considering a cost-benefit analysis framework for future research and implications. As it has been discussed, subsidizing the cost of vanpooling for employees who commute using vanpool could be one incentive, including also free parking for the vanpoolers. Another example is the vanpooling incentives provided by San Mateo County in California State. More specifically, vanpool participants are reimbursed 50% of the cost of their vanpool seat, per month, for the first three months in the van, while vanpool drivers for a new vanpool can earn a $500 incentive for the first use. Another example is that employees riding in commuter highway vehicles (vanpools) may claim a vanpool rider subsidy of 75% reimbursement of their monthly vanpool fees up to a maximum of $65 per month, which is provided by California State as an additional vanpool incentive. Moreover, in line with the previous, eligible employees driving over 50% of the time in vanpools may claim a vanpool incentive of $100 per month. These are just some of the examples of vanpool incentives provided by York County and other areas in USA, which can be useful for future implications.

To conclude, the paper's findings are consistent with Cutter and Neidell's (2009) results. Specifically, the authors examined the effects of "Spare the Air" advisory program and found significant decreases in traffic volume. Nevertheless, Cutter and Neidell's (2009) argue that the air quality can be further improved if the ozone warnings are associated with additionally incentives, as the vanpool program. On the other hand the study's findings are not in line with Cummings and Walker's (2000) results, where an advisory voluntary program is examined in the Atlanta of Georgia metropolitan area on hourly traffic volumes and the authors found statistically insignificant effects.

It should be noticed that our estimates identify only a local average treatment effect and may not generalize to advisories issued at other levels the effect we identify is of direct policy interest since it is the level at which air quality standards are violated. Therefore, how well the results generalize to other areas will greatly depend on local conditions. However, the important finding of this study is that the ozone warning system in association with the vanpool program can reduce even more the traffic volume, ozone levels and therefore infant mortality.

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Table 1. Ozone AQI categories

Ozone AQI value	1997 8-hour (ppb)	2008 8-hour (ppb)	AQI category	Ozone Health information
0 - 50	0-64	0-59	Good	None
51 - 100	65-84	60-75	Moderate	Unusually sensitive people should consider reducing prolonged or heavy exertion outdoors
101 - 150	85-104	76-95	Unhealthy for sensitive groups	Active children and adults, and people with lung disease, such as asthma, should reduce prolonged or heavy exertion outdoors.
151 - 200	105-124	96-115	Unhealthy	Active children and adults, and people with lung disease, such as asthma, should avoid prolonged or heavy exertion outdoors. Everyone else, especially children, should reduce prolonged or heavy exertion outdoors.
201 - 300	125-374	116-374	Very unhealthy	Active children and adults, and people with lung disease, such as asthma, should avoid all outdoor exertion. Everyone else, especially children, should avoid prolonged or heavy exertion outdoors.
301 - 500	>=375	>=375	Hazardous	Everyone should avoid all physical activity outdoors

Source - U.S. Environmental Protection Agency

Map 1. Control and Treatment Counties in South Carolina State

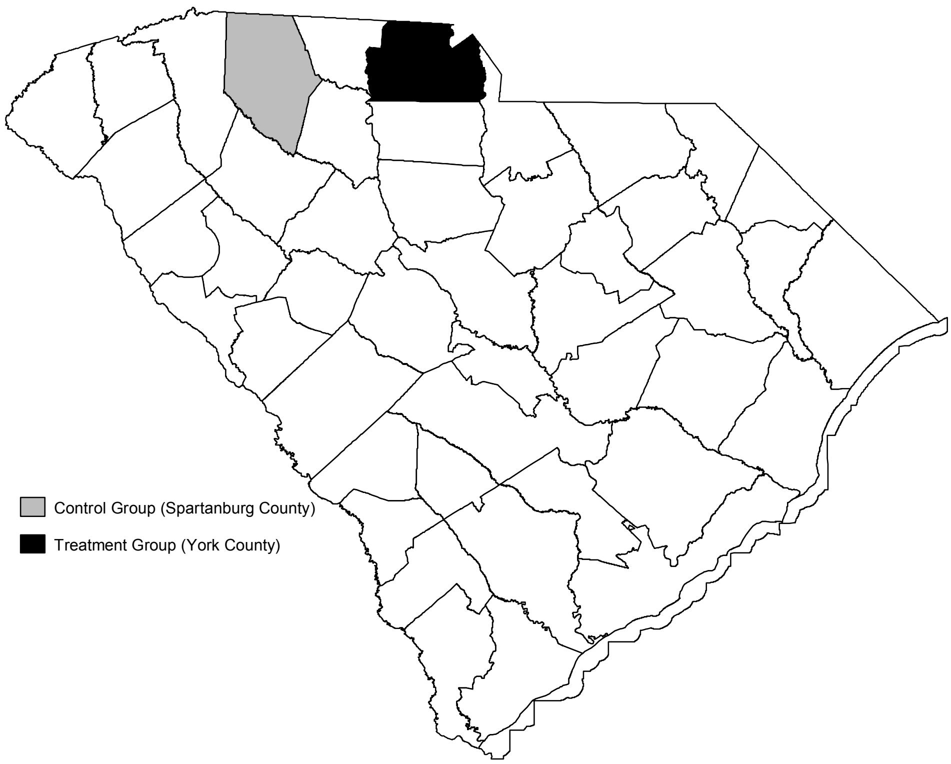

Figure 1. Kernel Density Distribution for Traffic Volume in York County

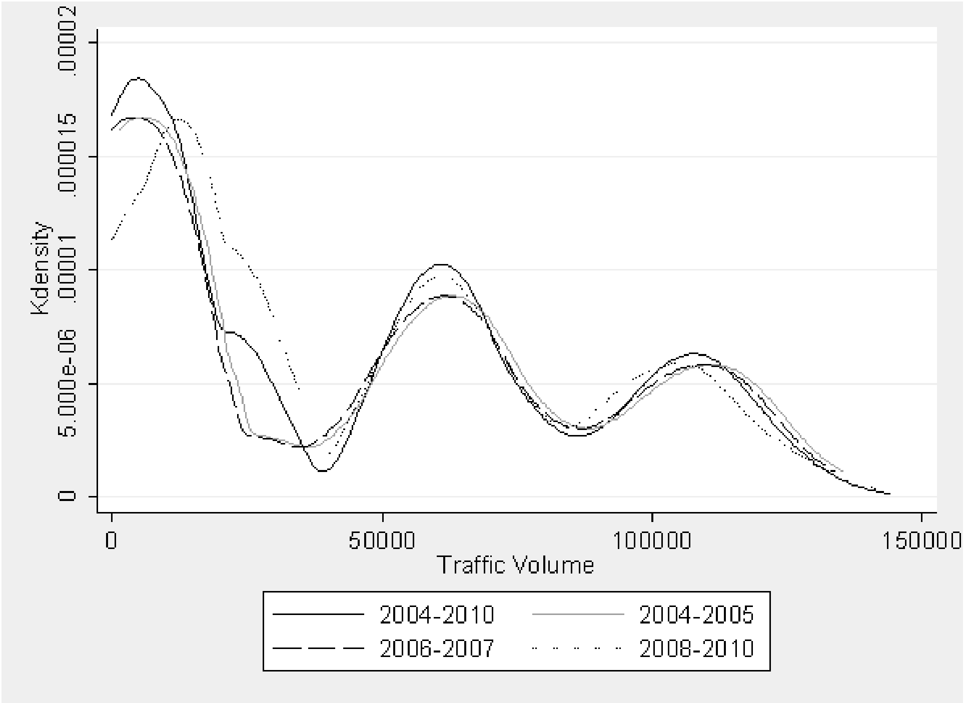

Figure 2. Kernel Density Distribution for Traffic Volume in Spartanburg County

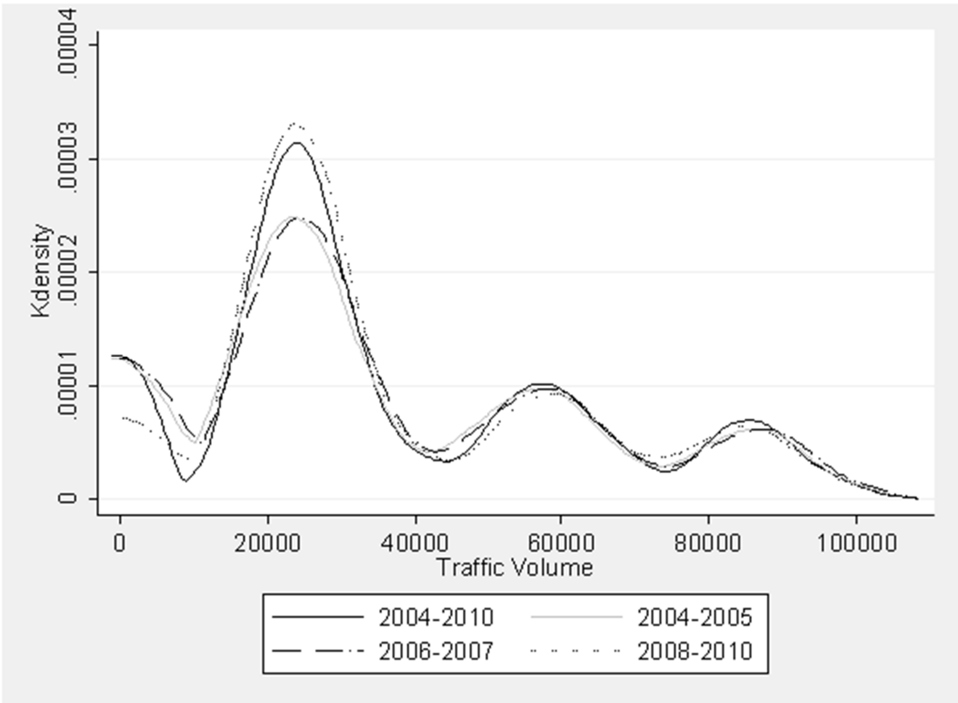

Table 2. Age Groups Population and Proportions for York and Spartanburg Counties during 2004-2010.

Year	Spartanburg County		York County		T-statistic
	Total Population		**Total Population**		**Total Population**
2004	253,793		221,614		
2005	259,224		225,143		
2006	271,087		249,035		1.511 (0.2774)
2007	275,534		258,827		
2008	280,738		267,448		
2009	286,822		277,003		
2010	286,868		280,528		
	20 to 24 years Levels	**20 to 24 years Proportion**	**20 to 24 years Levels**	**20 to 24 years Proportion**	**20 to 24 years**
2004	16,236	6.40%	14,405	6.50%	
2005	17,005	6.56%	15,580	6.92%	
2006	16,854	6.22%	16,509	6.63%	
2007	17,207	6.24%	17,250	6.66%	0.6672 (0.5367)
2008	17,642	6.28%	16,921	6.33%	
2009	18,696	6.52%	16,102	5.81%	
2010	20,141	7.02%	17,876	6.37%	
	25 to 34 years Levels	**25 to 34 years Proportion**	**25 to 34 years Levels**	**25 to 34 years Proportion**	**25 to 34 years**
2004	36,381	14.30%	31,691	14.30%	
2005	35,254	13.60%	31,970	14.20%	
2006	36,504	13.47%	30,529	12.26%	1.5143 (0.2206)
2007	36,267	13.16%	31,422	12.14%	
2008	35,727	12.73%	31,949	11.95%	
2009	35,287	12.30%	32,329	11.67%	
2010	32,191	11.22%	30,935	11.03%	
	35 to 44 years Levels	**35 to 44 years Proportion**	**35 to 44 years Levels**	**35 to 44 years Proportion**	**35 to 44 years**
2004	39,544	15.60%	37,010	16.70%	
2005	38,883	15.00%	35,122	15.60%	
2006	40,827	15.06%	35,342	14.19%	1.4016 (0.2960)
2007	40,288	14.62%	36,690	14.18%	
2008	40,407	14.39%	36,731	13.73%	
2009	39,227	13.68%	39,124	14.12%	
2010	39,461	13.76%	38,900	13.87%	

Table 2 (cont.) Age Groups Population and Proportions for York and Spartanburg Counties during 2004-2010.

Year	Spartanburg County		York County		t-statistic
	45 to 54 years Levels	**45 to 54 years Proportion**	**45 to 54 years Levels**	**45 to 54 years Proportion**	**45 to 54 years**
2004	35,616	14.10%	30,804	13.90%	1.5261 (0.2523)
2005	38,365	14.80%	33,096	14.70%	
2006	38,939	14.36%	34,536	13.87%	
2007	39,496	14.33%	36,051	13.93%	
2008	40,017	14.25%	38,135	14.26%	
2009	41,629	14.51%	39,540	14.27%	
2010	41,082	14.32%	39,825	14.20%	
	55 to 59 years Levels	**55 to 59 years Proportion**	**55 to 59 years Levels**	**55 to 59 years Proportion**	**55 to 59 years**
2004	16,541	6.52%	11,081	5.00%	1.3054 (0.3318)
2005	17,886	6.90%	11,933	5.30%	
2006	17,414	6.42%	14,461	6.21%	
2007	18,813	6.83%	14,179	6.48%	
2008	18,265	6.51%	14,514	6.23%	
2009	17,529	6.11%	13,813	5.99%	
2010	17,908	6.24%	16,943	6.04%	
	60 to 64 years Levels	**60 to 64 years Proportion**	**60 to 64 years Levels**	**60 to 64 years Proportion**	**60 to 64 years**
2004	10,688	4.20%	9,197	4.15%	1.8504 (0.1137)
2005	11,406	4.40%	10,807	4.80%	
2006	13,689	5.05%	11,012	4.42%	
2007	13,659	4.96%	12,571	4.86%	
2008	16,054	5.72%	14,136	5.29%	
2009	16,394	5.72%	14,444	5.21%	
2010	17,904	6.24%	13,889	4.95%	
	65 and over Levels	**65 and over Proportion**	**65 and over Levels**	**65 and over Proportion**	**65 and over**
2004	31,470	12.40%	23,270	10.50%	4.0987 (0.0222)**
2005	31,366	12.10%	25,216	11.20%	
2006	34,819	12.14%	28,655	11.51%	
2007	36,361	12.20%	29,229	11.29%	
2008	37,560	12.38%	31,010	11.59%	
2009	39,769	12.87%	34,185	12.34%	
2010	39,065	12.62%	33,662	12.00%	

Source United States Census Bureau http://www.census.gov, p-values between brackets, ** rejects the null hypothesis at 5% significance level

Table 3. Race Groups Population and Proportions for York and Spartanburg Counties during 2004-2010.

Year	Spartanburg County				York County				t-statistic
	White (Levels)	White (Proportion)	Asian (Levels)	Asian (Proportion)	White (Levels)	White (Proportion)	Asian (Levels)	Asian (Proportion)	White
2004	185,827	73.22%	3,959	1.56%	166,232	75.01%	3,280	1.48%	
2005	191,488	73.85%	4,370	1.69%	170,004	75.50%	3,354	1.49%	1.1585 (0.3907)
2006	195,575	72.14%	4,845	1.79%	179,442	71.88%	3,759	1.51%	
2007	209,503	76.04%	5,514	2.00%	185,167	71.84%	4,287	1.71%	
2008	214,085	76.26%	5,452	1.94%	194,617	72.65%	4,391	1.67%	
2009	202,827	70.72%	5,021	1.75%	195,966	70.39%	4,808	1.73%	**African American**
2010	214,964	74.93%	6,611	2.30%	203,525	72.50%	5,304	1.89%	1.3425 (0.2834)
	African American (Levels)	**African American (Proportion)**	**Hispanic or Latino (Levels)**	**Hispanic or Latino (Proportion)**	**African American (Levels)**	**African American (Proportion)**	**Hispanic or Latino (Levels)**	**Hispanic or Latino (Proportion)**	**Asian**
2004	49,641	19.56%	10,431	4.11%	46,096	20.80%	8,133	3.67%	2.385 (0.0546)*
2005	52,187	20.13%	11,179	4.31%	45,132	20.05%	8,375	3.71%	
2006	54,216	20.01%	12,148	4.48%	49,805	19.99%	9,292	3.73%	**Hispanic or Latino**
2007	56,494	20.57%	12,719	4.62%	52,034	20.24%	10,704	4.14%	1.6002 (0.1210)
2008	57,936	20.63%	14,201	5.06%	52,903	19.81%	11,601	4.34%	
2009	57,997	20.22%	16,191	5.64%	54,967	19.84%	12,856	4.64%	
2010	56,396	19.65%	17,500	6.10%	54,494	19.46%	14,799	5.92%	

Table 3 (cont.) Race Groups Population and Proportions for York and Spartanburg Counties during 2006-2010.

Year	Spartanburg County				York County				t-statistic
	American Indian (Levels)	**American Indian (Proportion)**	**Some other race (Levels)**	**Some other race (Proportion)**	**American Indian (Levels)**	**American Indian (Proportion)**	**Some other race (Levels)**	**Some other race (Proportion)**	**American Indian**
2004	508	0.20%	812	0.32%	931	0.42%	909	0.41%	-0.6976 (0.5115)
2005	570	0.22%	669	0.25%	1,018	0.46%	993	0.44%	
2006	557	0.21%	463	0.17%	1,208	0.49%	1,378	0.55%	
2007	1,365	0.50%	1,827	0.66%	1,161	0.45%	2,844	1.10%	**Some other race**
2008	1,928	0.69%	1,290	0.46%	450	0.17%	571	0.21%	-1.2927 (0.2437)
2009	604	0.21%	239	0.08%	1,315	0.47%	2,150	0.78%	
2010	1,886	0.66%	4,332	1.51%	2,122	0.76%	3,397	1.21%	

Source United States Census Bureau http://www.census.gov, p-values between brackets, * rejects the null hypothesis at 10% significance level

Table 4. Number of Firms and Employees in Major Industry Sectors York and Spartanburg Counties during 2004-2010.

Year	Spartanburg County		York County		t-statistic (Number of Firms)	t-statistic (Number of employees)
	Construction (Number of firms)	**Construction (Number of employees)**	**Construction (Number of firms)**	**Construction (Number of employees)**	**Construction (Number of firms)**	**Construction (Number of employees)**
2004	736	5,310	555	3,978		
2005	722	5,696	559	4,103		
2006	727	5,460	383	5,046	2.5270 (0.0321)**	1.1014 (0.2110)
2007	716	7,048	585	6,141		
2008	633	5,846	575	5,969		
2009	577	5,236	426	5,496		
2010	517	5,284	415	5,249		
	Manufacturing (Number of firms)	**Manufacturing (Number of employees)**	**Manufacturing (Number of firms)**	**Manufacturing (Number of employees)**	**Manufacturing (Number of firms)**	**Manufacturing (Number of employees)**
2004	636	23,889	517	20,270		
2005	646	25,743	529	21,438		
2006	686	26,270	574	24,636	1.5947 (0.1410)	1.3777 (0.1988)
2007	458	26,819	442	24,057		
2008	437	23,852	425	21,569		
2009	420	22,653	412	21,936		
2010	401	22,512	396	21,232		

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Table 4 (cont.) Number of Firms and Employees in Major Industry Sectors York and Spartanburg Counties during 2006-2010**.**

Year	**Spartanburg County**		**York County**		**t-statistic (Number of Firms)**	**t-statistic (Number of employees)**
	Agriculture, forestry (Number of firms)	**Agriculture, forestry (Number of employees)**	**Agriculture, forestry (Number of firms)**	**Agriculture, forestry (Number of employees)**	**Agriculture, forestry (Number of firms)**	**Agriculture, forestry (Number of employees)**
2004	17	48	20	49		
2005	17	43	18	32		
2006	19	43	25	39	-1.479 (0.1411)	-0.8332 (0.4366)
2007	17	61	20	86		
2008	16	61	18	56		
2009	15	46	16	52		
2010	15	46	17	62		
	Utilities (Number of firms)	**Utilities (Number of employees)**	**Utilities (Number of firms)**	**Utilities (Number of employees)**	**Utilities (Number of firms)**	**Utilities (Number of employees)**
2004	32	115	29	112		
2005	38	139	31	124		
2006	38	141	35	127	1.183 (0.2989)	1.9113 (0.1045)
2007	37	132	33	122		
2008	37	127	33	122		
2009	28	97	26	104		
2010	28	97	25	97		

Table 4 (cont.) Number of Firms and Employees in Major Industry Sectors York and Spartanburg Counties during 2006-2010.

Year	**Spartanburg County**				**York County**				**t-statistic (Number of Firms)**	**t-statistic (Number of employees)**
	Finance-Insurance (Number of firms)	**Finance-Insurance (Number of employees)**	**Wholesale-Retail Trade (Number of firms)**	**Wholesale-Retail Trade (Number of employees)**	**Finance-Insurance (Number of firms)**	**Finance-Insurance (Number of employees)**	**Wholesale-Retail Trade (Number of firms)**	**Wholesale-Retail Trade (Number of employees)**	**Finance-Insurance (Number of firms)**	**Finance-Insurance (Number of employees)**
2004	426	3,105	3,109	19,105	413	5,033	2,530	18,971	1.5241 (0.1783)	-13.569 (0.000)***
2005	431	3,150	3,123	20,087	423	5,817	2,570	18,446		
2006	465	2,524	3,138	20,568	455	6,111	2,585	19,526		
2007	448	2,632	2,867	20,798	451	5,486	2,628	19,249	**Wholesale-Retail Trade (Number of firms)**	**Wholesale-Retail Trade (Number of employees)**
2008	454	2,433	1,538	19,905	444	5,350	1,417	18,959	1.8447 (0.1189)	4.4601 (0.0016)***
2009	427	2,267	1,520	19,647	419	5,863	1,331	18,834		
2010	413	2,224	1,488	19,750	424	5,357	1,306	18,635		

Source United States Census Bureau http://www.census.gov, p-values between brackets, ***, ** and * reject the null hypothesis at 1%, 5% and 10% significance level

Table 5. Unemployment Rate, Mean Household Income and Population Proportion of Income in York and Spartanburg Counties during 2006-2010

County	Year	Unemployment Rate	Per Capita Income	t-statistics
Spartanburg	2004	7.60%	22,139	**Unemployment Rate**
Spartanburg	2005	7.50%	22,878	0.5930 (0.5811)
Spartanburg	2006	7.11%	23,510	
Spartanburg	2007	4.20%	24,657	
Spartanburg	2008	4.80%	24,451	**Per Capita Income**
Spartanburg	2009	6.80%	23,148	-1.6101 (0.2112)
Spartanburg	2010	7.50%	22,964	
York	2004	7.20%	22,572	
York	2005	6.70%	23,101	
York	2006	5.58%	23,523	
York	2007	5.00%	24,959	
York	2008	5.10%	25,204	
York	2009	6.80%	24,241	
York	2010	7.90%	23,660	

Source United States Census Bureau http://www.census.gov, p-values between brackets

Table 6. Quadruple DID Estimates of Equation (1)

	(1)	(2)	(3)	(4)
Panel A; All Days of the Week				
	Total Hours		Peak Hours	
β5 (DD)	-702.243*** (249.880)	-697.033** (285.251)	-789.135*** (242.249)	-740.452** (298.131)
β12 (DDD)	-240.962** (115.356)	-218.713** (101.625)	-283.340** (137.518)	-233.929** (114.558)
β14 (DDDD)	-47.842** (21.538)	- 40.087* (21.256)	-68.483** (33.037)	-57.098* (31.171)
R^2	0.8152		0.8476	
Wald Statistic		2,718.13 [0.000]		2,736.55 [0.000]
obs	21,790	21,680	21,790	21,680
Panel B: Between Monday-Friday				
	Total Hours		Peak Hours	
β5 (DD)	-780.732** (360.512)	-735.621** (324.276)	-819.657*** (306.526)	-788.367** (317.144)
β12 (DDD)	-258.167** (121.205)	-232.496** (110.278)	-296.068** (143.744)	-255.121** (121.757)
β14 (DDDD)	-59.354** (24.315)	-47.456** (22.382)	-84.757** (38.264)	-57.638* (32.252)
R^2	0.8261		0.8873	
Wald Statistic		2,770.28 [0.000]		2,785.26 [0.000]
obs	15,529	15,451	15,529	15,451

a. Standard errors are reported between brackets, standard errors are clustered on traffic monitoring site, p-values between square brackets
b. The dependent variable is the traffic volume and the control variables are traffic sites, counties, day of the week, month, year, average temperature, humidity, precipitation and wind speed
c. ***, ** and * denote significance at the 1% , 5% and 10% level.
d. Estimations in columns (1) and (3) refer to quadruple DID estimated with static Fixed effects, while estimations (2) and (4) refer to quadruple DID estimated with GMM.

Table 7. Robustness checks for DID regressions (2)-(3)

Panel A:Robustness Check Using Placebo Dummies Before the Treatment Regression (2)			
	Total Hours	Peak Hours	
DD	112.367 (377.009)	126.732 (321.664)	
R^2	0.8813	0.8767	
Wald Statistic			
obs	3,660	3,660	
Panel B:Robustness Check Using Leads and Lags Regression (3)			
	Total Hours		
DD_{t-1}	-761.931** (365.898)	-733.812** (263.461)	-717.348** (334.274)
DD_{t-2}		-740.87** (303.945)	-732.497** (321.361)
DD_{t-3}			-755.597* (355.991)
DD_{t+1}	-193.576 (367.232)	-124.782 (325.571)	-160.16 (307.75)
DD_{t+2}		171.983 (468.603)	197.080 (451.51)
DD_{t+3}			98.809 (84.97)
R^2	0.8787	0.8788	0.8788
obs	21,698	21,692	21,688
	Peak Hours		
DD_{t-1}	-812.628** (382.803)	-801.077** (397.435)	-787.837** (391.808)
DD_{t-2}		-820.87* (433.945)	-792.497* (404.361)
DD_{t-3}			-807.671* (413.388)
DD_{t+1}	-141.628 (361.283)	-115.330 (358.285)	-124.158 (329.592)
DD_{t+2}		174.332 (414.120)	155.562 (438.785)
DD_{t+3}			87.218 (92.386)
R^2	0.8771	0.8781	0.8788
obs	21,698	21,592	21,488

a. Standard errors are reported between brackets, standard errors are clustered on traffic monitoring site, p-values between square brackets
b. The dependent variable is the traffic volume and the control variables are traffic sites, counties, day of the week, month, year, average temperature, humidity, precipitation and wind speed
c. ***, ** and * denote significance at the 1%, 5% and 10% level.

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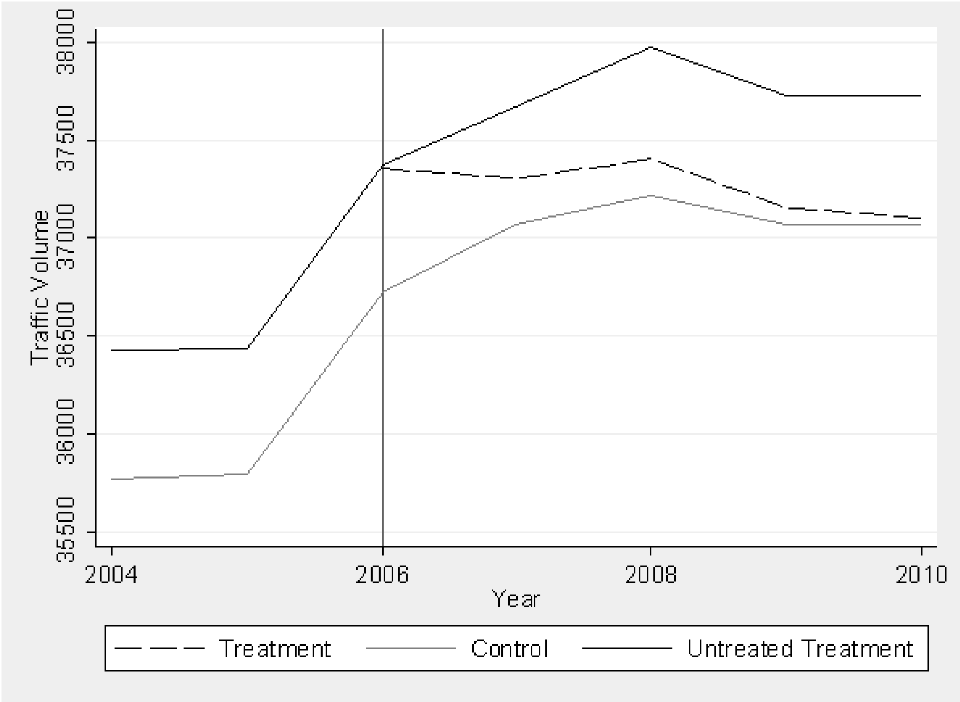
Figure 3. DID Estimates for the Vanpool Program



Chapter Three

Relationship between Recycling Rate and Air Pollution: Evidence from Waste Management Municipality Survey in the State of Massachusetts

Eleftherios Giovanis[*]

Abstract

Recycling can be an effective tool for reducing waste generation, eliminating waste disposal sent in landfills and incinerators and reducing environmental pollution. Moreover, recycling is one way to achieve sustainable use of natural resources and to protect the environment and human health. However, the relationship between air pollution and recycling has been neglected in the previous economic studies. This study examines this relationship using panel data from a waste municipality survey in the state of Massachusetts during the period 2009-2012. In addition, the analysis considers economic factors, as unemployment rate and income per capita, meteorological variables, as well as, it accounts for additional municipality characteristics, such as population density and trash collection services. The approach followed is a fixed effects model which controls for stable time invariant characteristics of the municipalities, thereby eliminating potentially large sources of bias. The findings support that a negative relationship between recycling rate and particulate particles in the air of 2.5 micrometres or less in size ($PM_{2.5}$) is present.

Keywords: Air Pollution, Data, Municipality Survey, Recycling, Solid waste services, Stochastic Frontier Analysis

JEL Codes: Q50, Q53

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1. Introduction

Recycling is the process of collecting and processing materials that would otherwise be thrown away as trash and turning them into new products. According to the U.S. Environmental Protection Agency (EPA), recycling helps the economy and the environment (EPA, 2007; 2009). Manufacturing products from recycled materials consume less energy and produce less pollution than producing the same items from virgin materials. Reducing the use of virgin materials conserves natural resources like trees, water and minerals. In addition, by reducing the amount of waste sent to landfills and incinerators the air quality is improved.

The environmental economics literature pays attention to the waste management services cost structure rather than to the relationship between pollution, waste management and recycling. Numerous scientific studies have linked particle pollution exposure to a variety of negative outcomes, including premature death for people with heart or lung disease, nonfatal heart attacks, irregular heartbeat, aggravated asthma, decreased lung function, and increased respiratory symptoms (Seaton et al., 1995; Nel et al., 1998; Harrison and Yin, 2000; Vrijheid, 2000; Li et al., 2002; Li et al., 2003; Sarnat et al., 2005).

This paper proposes an econometric model to test and describe how municipal recycling rate is associated to air pollution, and specifically to particulate matter less than 2.5 micrometers in diameter ($PM_{2.5}$). $PM_{2.5}$ is one of the six most common air pollutants including CO, SO_2, NO_X, Lead and Ground-Level Ozone. The paper focuses on $PM_{2.,5}$ as it is better monitored than other pollutants (21 monitoring stations vs 7) throughout the state of Massachusetts, for which this analysis is done. Data on recycling is obtained for 325 municipalities and cities in the state of Massachusetts from municipality surveys during the period 2009-2012.

The first contribution is that it is the first study which examines the relationship between recycling and air pollution. Another contribution is that the analysis expands on the cross-sectional data analysis of Hirsch (1965) and Bel and Fageda (2010) and relies on panel data. Cross-sectional data, used in previous studies, are likely to lead to biased estimates due to unobservable characteristics which are correlated both with pollution and recycling. Panel data makes it possible to control for unobserved cross section heterogeneity, i.e. taking into account unobserved individual or time effects, such as years, by including them in the model (Wooldridge, 2010). In addition, this study considers additional factors, including income per capita, population density, trash collection services and Pay-as-you-Throw (PAYT) program. The overall results show that recycling improves air quality by reducing $PM_{2.5}$ pollutant emissions.

The structure of the paper is as follows. The second section presents the literature review. It reviews theoretical and empirical studies on solid waste management. Section three presents the data; section four discusses the methodology used in the analysis of solid waste services, while in section five the empirical results and recommendations are reported and discussed. In section six the conclusions are presented.

2. Literature review

This section presents previous research studies on recycling, disposal, waste management costs and recycling programs from the economics field. These studies do not examine the relationship between air pollution and recycling; however are discussed here because these are closer to the analysis employed in this study.

One of the first studies employed the relationship between recycling and disposal in a theoretical framework is by Smith (1972) who treats recycling as a reprocessing of the residue from consumption. The reprocessing activity represents a utility loss, i.e. a negative effect upon consumers' utility. Specifically, forcing consumers to retain pollutants such as aluminum cans or glass bottles can represent a loss of utility when disposal is considered a costly activity by the consumers. Consumers will bear these costs if there are returns in form of reduced pollution so they need to be informed of the returns in order to change their behaviour. On the other hand, Plourde (1972) treats recycling as a productive process intended to decrease the stock of pollution, which results from the accumulation of waste that accompanies production and consumption. The approach is different from Smith (1972), and uses a central planner optimization problem through taxation. Pollution, having undesirable effects on consumers, leads to a reallocation of resources to reduce its quantity. Neither of these papers provide empirical evidence.

A similar study with the current one is by Kinnaman et al. (2010); however the relationship between recycling and cost instead of air pollution is examined. Kinnaman et al. (2010) used Japanese data and fixed effects model in order to estimate the social cost of municipal waste management as a function of the recycling rate. Kinnaman et al. (2010) found a quadratic relationship between waste management costs and the recycling rate and more specifically an inverted U-shaped curve. Additionally the authors examine the relationship between municipal waste management cost and recycling rate for different product categories, finding mixed results, either linear or quadratic significant effects. Similarly to the research by Kinnaman et al. (2010), this study employs a fixed effects model.

A study which examines the recycling schemes and rates in the state of Massachusetts is by Russell (2011). Russell (2011) found that the type of collection, curbside, drop-off, single-stream, or pay-as-you-throw (PAYT), has an impact on the success of the recycling program. PAYT and single-stream systems were shown to increase recycling rates, while the residents who live in towns with drop-off programs actually recycle more material than those in towns with curbside service. According to a study released recently by the New York-based Green Waste Solutions and the U.S. Environmental Protection Agency (EPA, 2010) local governments with PAYT programs produce 467 pounds of landfilled trash per capita per year, compared with 918 pounds in non-PAYT communities. In Massachusetts, cities and towns with PAYT programs produce approximately 0.56 tons of trash per household compared to 1.13 tons for non-PAYT communities. In addition, PAYT can be applied either on drop off or curbside service. It was noted, that drop off service is more efficient than curbside is. Roughly 45 per cent of the municipalities, employing PAYT program, offers only the drop off service, while the 37 per cent offers only the curbside service. Therefore, increasing the drop off service in municipalities following the PAYT system might improve the air quality. Furthermore, it was found that municipalities applying both drop off and curbside recycling collection services have a greater positive impact on air quality. So, another suggestion could be for municipalities to offer both services. The characteristics and the effects of the PAYT program are discussed in more details in the results part. A very similar study is by Kuhn and Schulz (2003) who found that environmental quality is negatively affected by the amount of waste dumped and the amount of resources extracted. In addition, the authors show that balanced sustainable growth is only possible if governmental policy ensures a recycling rate of 100%.

In line with these results, this study contributes to the literature of economics field by examining the relationship between air pollution and recycling controlling for various economic factors, meteorological data and other trash collection and recycling programs characteristics among others.

On the other hand, regarding the environmental engineering and chemistry literature a positive and significant association between particulate matter and landfilling has been found (Fitz and Bumiller, 2000; Stevenson, 2002; Chalvatzaki et al., 2010). Chalvatzaki et al. (2010) examining a landfill site in Crete of Greece found that particulate matter emissions are significant. Those emissions in landfills are the result of re-suspension from the disposed waste and other activities as composting, waste unloading and sorting and waste transport by trucks. These studies control additionally for weather conditions, such as temperature and wind speed. However, this study adds to this literature by accounting for additional demographic and economic factors, as well as, for trash and recycling programs.

3. Data

The data used in this study come from various sources. More specifically, the solid waste municipality survey, the recycling rates and the air pollution data for $PM_{2.5}$ can be found at the Massachusetts Department of Environmental Protection website for the period 2009-2012. $PM_{2.5}$ is measured as the average pollution over a yearly period. It should be noted that according to the US Environmental Protection Agency (EPA) there are no areas in the state of Massachusetts which violate the air quality standards regarding particulate matters. The municipal solid waste (MSW) recycling rate is calculated by the Massachusetts Department of Environmental Protection as:

$$MSW\ \ recycling\ \ rate = \frac{Total\ \ MSW\ \ recycled}{Total\ \ MSW\ \ generated} \tag{1}$$

Total MSW generated = MSW recycled + MSW disposed as trash. This ratio is calculated separately for different product but especially hazardous products, like batteries, computers and electronic equipment, and conversion factors are used to convert values into tons, so that they can be aggregated.

Particulate matter ($PM_{2.5}$) is a complex mixture of extremely small particles and liquid droplets. Particle pollution is made up of a number of components, including acids (such as nitrates and sulfates), organic chemicals, metals, and soil or dust particles. According to EPA (2000) the principal sources of $PM_{2.5}$ emissions are miscellaneous sources, such as highway and off-road vehicles, waste disposal, industrial sources and fuel combustion at stationary sources such as apartment buildings, hospitals and office buildings. In addition, particulate matter emissions are generated by combustion devices used to reduce air emissions from landfills. Thus, on the one hand, particulate matter is emitted from landfills, while on the other hand are emitted through combustion process (EPA, 1995; 2008; Fitz and Bumiller, 2000; Stevenson, 2002; Psomopoulos et al., 2009; Koshy et al., 2009; Chalvatzaki et al., 2010).

Generally, the link between $PM_{2.5}$ and landfills is formed on the action of tipping waste which raises plumes of dust, notably on elevated ground, which are exposed to windy conditions, on the waste compaction by bulldozers and crushers. Finally $PM_{2.5}$ is formed on the stockpiles of soil and rubble required for daily waste coverage which are susceptible to re-suspension and dispersion by wind flow (Koshy et al., 2009; Chalvatzaki et al., 2010).

In map 1 the air monitoring stations for $PM_{2.5}$ are reported. Regarding mapping the $PM_{2.5}$ to each municipality, the following approach is followed. Firstly, the exact location of each monitoring station in terms of longitude and latitude coordinates is found. Secondly, the centroid coordinates of each municipality is given. The next step is to compute the nearest neighbours using geodetic distances, and specifically the Haversine formula[3] and matching each monitoring station to the closest centroid

[3]Haversine formula has been used which is:
First step: R = 637100 (the Earth's radius in meters)
Second step: Δlatitude = $\text{latitude}_1 - \text{latitude}_2$
Third step: Δlongitude = $\text{longitude}_1 - \text{longitude}_2$

without imposing any restriction on how far from a monitoring station the municipality can be[4]. The reason why Haversine formula is preferred over the Euclidean is the following: Euclidean distance is a good approximation for short distances, such as between cities, normally within 10-15 km. However, for longer distances, such as between counties, measures based on two dimensions, as the Euclidean distance, are no longer appropriate, since they fail to account for the curvature of the earth. (Robusto, 1957; Sinnott, 1984).

The population density has been retrieved from the Massachusetts Executive Office for Administration and Finance. The income per capita for each municipality comes from the Massachusetts Department of Revenue (DOR), while the unemployment rates have been retrieved from the Massachusetts Executive Office of Labor and Workforce Development. The meteorological data-average, minimum and maximum temperature, wind speed and precipitation- can be found at Tutiempo weather and the US National Climatic DataCenter (NCDC). The study period is 2009-2012 and the data are based on yearly frequency. Note that no day above the threshold triggering a smog alert was reported during the period examined. It should be noted, that the traffic volume counts could have been used, but the data are available only up to 2009. More specifically, the variables included in the model are: *Population Density*. This variable is derived by dividing the municipality population, which is included by itself, by the land area size. The second variable is the *Income per capita* for each municipality. The sign might be positive, as a higher income implies higher consumption and additional waste and pollution. However, based on the Environmental Kuznets Curve (EKC) hypothesis the relationship between air pollution and income can be an inverted U-shaped curve.

Fourth step: $a = \sin^2(\Delta\text{latitude} / 2) + \cos(\text{latitude}_1) \cdot \cos(\text{latitude}_2) \cdot \sin^2(\Delta\text{longitude} / 2)$

Fifth step: $c = 2 \cdot \text{atan2}(\sqrt{\alpha}, \sqrt{1-\alpha})$

Sixth step: distance = $R \cdot c$

[4]The results for specific distance between municipality and monitoring station using the inverse weighting distance ie.within 10 or 20 miles show the same negative relationship between recycling and air pollution; however the effects become stronger when a municipality is located closer to a monitoring station.

Unemployment rate in each municipality is another variable used in the analysis. This can be negative as a higher unemployment rate implies less purchasing power; therefore less waste volume, as well as, less air emissions caused by transportation to work.

The next two variables are the *Reciprocal and Regional Program*: The former is a dummy taking the value 1 if there is a reciprocal program in the municipality and 0 otherwise. More precisely, this program refers to a reciprocal use agreement with other municipalities to allow their residents to deliver waste and problem materials to the municipality's permanent facilities and event collection sites. Similarly, *Regional program* is a dummy taking the value 1 if there is a regional program in the municipality and 0 otherwise. However, these variables are potentially endogenous. For this reason, initially the model is estimated without the potential endogenous variables and then including all of them. The next variables refer to *trash, yard* and *food waste service types*. These are categorical variables taking four values; if there is a drop off service, if there is curbside service if there are both services and neither of the above. In a curbside recycling program, recyclable materials, such as cans and bottles, are placed in special containers at the curb for pickup by a recycling truck. A drop off recycling program provides a centre where citizens can transport and drop off their recyclable materials. Where appropriate, the index of these variables is: 1 for curbside, 2 for drop-off and 3 for none of the above. Because reciprocal and regional program, as well as, trash, food and yard waste service type are possibly endogenous the estimates take place without and with them. *Meteorological data* are considered in the analysis too. It is expected that $PM_{2.5}$ is negatively associated to minimum temperature, precipitation and wind speed, while a positive sign is expected for average and maximum temperature (Tai et al., 2010; Chalvatzaki et al., 2010; Barmpadimos et al., 2012; Lecoeur et al., 2012; Tai et al., 2012). We obtain the average values over a year of the above meteorological variables. *Combustion*, is a dummy variable taking value 1 if there is a combustion-incineration plant in the municipality and 0 otherwise. It should be noted that the incineration process is not considered as recycling, but is a process which is used to minimise the generation of wastes and reduce landfilling. This variable is taken into consideration, because incinerators are one of the sources of $PM_{2.5}$ in Massachusetts (Massachusetts Department of Public Health, http://www.mass.gov/eohhs/gov/departments/dph/).

Landfill is a categorical variable taking four values; 1 for no-landfill in the specific municipality, 2 if both are private, 3 if one is private and 4 if both are public. This is measured to examine which regime-public or private- is more efficient in generating air quality, as in the literature used to examine the efficiency of waste management service costs (Hirsch, 1965; Kemper and Quigley, 1976; Collins and Downes, 1977; Bel and Fageda, 2010). *Municipality Type* is a dummy variable indicating whether the municipality is a city or a town. The distinction between a city and a town as defined in Massachusetts law is primarily related to the form of government that the municipality has chosen[5]. Finally, *PAYT* is considered in the analysis, which is a dummy variable taking value 1 if there is PAYT (Pay-as-you-throw) program and 0 otherwise. In PAYT program residents are charged for each community-issued bag or container of waste they set out for disposal, and the residents have a variety of bag and container sizes from which to choose.

In table 1, summary statistics separately for every year are reported after reweighting municipalities by their population size. The average recycling rate has increased by 3 percentage points from 2009 to 2012, while the average air pollution ($PM_{2.5}$) decreased from 2009 to 2012 by 12%. In addition, the income per capita and unemployment rate have increased and decreased respectively from 2009 to 2012. In

[5]More specifically, a town is governed under the Town Meeting or Representative Town Meeting form of government. A city has a council or board of aldermen and may or may not have a mayor, a city manager, or both (State Street Trust Company, 1922).

figure 1 a scatter-plot is presented. Figure 1 shows the relationship between $PM_{2.5}$ and recycling rates, indicating a negative association. In addition, an outlier is observed in the right side of figure 1, was excluded, but this does alter the conclusion[6]. In map 2 the recycling rates at municipality level during 2009 are presented. Based on map 2, the majority of the municipalities located in western region are characterized by high recycling rates, while the municipalities located in the centre and north of the state are characterized by low recycling rates. The situation regarding the eastern part of the state of Massachusetts is mixed.

In table 2 the correlation matrix is presented. The correlation between total trash tonnage and $PM_{2.5}$ is positive but statistically insignificant. The correlation between population density and total trash tonnage is positive. Therefore, one assumption is that the higher the population density the higher the trash tonnage might be and so the higher the air pollution is expected to be from waste generation and landfilling depending on the recycling rates and traffic density among other factors. Regarding recycling rates, population density is positively correlated with recycling. In addition, the relationship between recycling rates and income per capita is positive, indicating that the higher the income is the higher the recycling rates are expected to be.

4. Econometric framework

In this section the econometric framework followed in this study is presented. By including fixed effects (group dummies for municipalities), the average differences across municipalities in any observable or unobservable predictors are controlled. These

[6] It is decided to keep this outlier. It should be noticed that the change in coefficients are considerable very small ie. The coefficient of recycling rate on air pollution is -0.0210 without the outlier, while it becomes -0.0211 including the outlier.

differences can include traffic, industrial activity and other factors that might affect the dependent variable- air pollution emissions. If the regressions are estimated with plain ordinary least squares (OLS) then there is a great worry that omitted variable bias would result because unobservable factors can be correlated with the variables that are included in the regression. The fixed effect coefficients soak up all the across-group action. What is left over is the within-group action, which is what is desirable and the threat of omitted variable bias has been reduced a lot. The following fixed effects model is estimated:[7]

$$\ln pm_{ijt} = \beta_0 + \beta_1 \text{lnrec\_rate}_{it} + \gamma_z' \ln W_{it} + \delta_z' X_{it} + \mu_i + l_j + \theta_t + \varepsilon_{ijt} \qquad (2)$$

Variable *pm* is the $PM_{2.5}$ emissions, *rec_rate* is the recycling rate, subscript *i* represents the municipality, subscript *j* denotes the air pollution monitoring site for $PM_{2.5}$ and subscript *t* indicates the year. Vector *W* includes meteorological variables as minimum, maximum and average temperature, precipitation and wind speed. Vector *X* includes the additional factors presented in the data section (note all the quantitative variables are expressed in logarithms). Finally, the vector μ_i includes municipality dummy variables, while l_j and θ_t control for air pollution monitoring stations and year fixed effects respectively.

Initially, the regressions excludes the dummies for reciprocal and regional program and the dummies representing the trash, food and yard waste services, as those are potentially endogenous. In addition, this study aims to provide a detailed empirical analysis of the factors that determine air pollution levels through waste services, like curbside, drop-off, and meteorological data. More specifically, many factors contribute to the success of municipal recycling programs, both demographic as well as the type of program in place. There are several different types of recycling programs a town can

[7] Based on Hausman test the fixed effects model is chosen.

implement, such as a curbside program, Pay-As-You-Throw (PAYT), or single stream program. Demographic factors, including population density, income, unemployment rate and location might have an impact on the local recycling rate and the air pollution.

In addition, a quadratic function of income per capita is included as in Grossman and Krueger (1993; 1995), Panayotou (1997) and Verneke and Clercq (2006) who examined the Environmental Kuznets Curve (EKC) hypothesis. This hypothesis explores the relationship between air pollution and income. The above-mentioned studies found an inverted U-shaped curve, indicating that the positive relationship between air emissions and income is inverted after a given point of income. By studying all of these different factors, this study looks to determine what actions can be taken by towns to increase their residential recycling rates and improve air quality.

5. Empirical results

In table 3 the fixed effects estimates are reported. Based on Hausman test the fixed effects model over the random effects model is chosen. The relationship between recycling rate and $PM_{2.5}$ is negative and significant in both estimates and the coefficient ranges between -0.021 and -0.024. Thus, for a 1 per cent increase in recycling rates the air pollution is decreased by 0.021-0.024 per cent or 0.0017-0019 micrograms per cubic meter ($\mu g/m^3$). This relationship between air pollution and recycling can be explained by various factors. Firstly, recycling can be one of the most effective ways to reduce the reliance and waste on landfills. By recycling, natural resources are conserved and the amount of pollution released into the environment is reduced. Also the impacts of landfills are greater than simply the space they take up. As organic matter breaks down in a landfill, it produces air pollution. This is also confirmed by the total trash tonnage, which increases air pollution and it is significant in both estimates. Local and State governments have to set up efficient recycling programs to capture bottles, cans, paper and other materials that are dumped into the garbage. Secondly, manufacturing products from recycled materials often generate less air pollution than what would have been generated when the product was made from the original materials. For example each glass bottle recycled keeps valuable non-renewable resources such as bauxite, iron-ore and sand in the ground. Making new glass from recycled cullet saves energy because recycled glass melts at a lower temperature than virgin raw materials. Because the materials do not need to be heated as much, less energy is required in the manufacturing process. Also, because recycled glass takes less energy to manufacture, finite natural resources such as oil and coal are also conserved (Morris, 1996). Thirdly, recycling reduces the incineration process as this process is associated with generating energy and electricity by burning materials, through which air pollutants are emitted (Morris, 1996). Recycling waste materials conserves energy by replacing virgin raw materials in manufacturing products, thereby reducing acquisition of virgin materials from the natural environment. Recycling most materials from municipal solid waste saves on average three to five times more energy than does burning them for electricity (Morris, 1996).

The income per capita is reported in quadratic terms, since higher polynomial orders have been found insignificant. We find an inverted U-shaped curve of the relationship between income per capita and pollution, similar to other studies (Grossman and Krueger, 1993; 1995, Panayotou, 1997, Verneke and Clercq, 2006). More specifically, the turning points range between \$23,000-\$26,000 average municipal income. Shafik and Bandyopadhyay (1992) found that the turning points for sulphur dioxide and carbon monoxide emissions range between \$2,200 and \$14,400 in 2009 prices. Selden and Song (1994) estimated EKCs for sulphur dioxide, nitrogen oxides and carbon monoxide using longitudinal data on emissions in developed countries. They found turning points equal at $17,300 for sulphur dioxide, $22,300 for nitrogen oxides, and $11,100 for CO in 2009 prices. Grossman and Krueger (1993) report turning points equal at $8,900 and $11,060 in 2009 prices for sulphur dioxide and nitrogen oxides respectively using data from the Global Environmental Monitoring System (GEMS) in 126 cities in 74 countries.

Unemployment rate has a positive effect on air quality; a quadratic term was tested but was never significant. Similarly, for population density, the quadratic term was, as in other studies (Skene et al., 2010; Clark et al. 2011) not significant; therefore only the linear term is considered. The results show that population density leads to reduced air pollution. Regional transportation plans, public officials, and urban planners have been seeking to densify urban areas, using strategies referred to as “smart growth” or “livability.” They have claimed that densifying urban areas would lead to lower levels of air pollution, principally because it is believed to reduce travel by car.

From table 3 the PAYT seems to have a positive impact on air quality, where the air pollution is less by 0.026 per cent less in municipalities, which employ PAYT system in comparison to those which do not. It should be noted that the average recycling rate is 33.75 per cent in the municipalities, where the PAYT system is implemented. On the other hand the recycling rate in municipalities with no PAYT system is 25.68 per cent. In some communities, PAYT works on a per-container basis; households are charged for each bag or can of waste they generate. A few communities bill residents based on the weight of their trash. Either way, the system motivates people to recycle more and think about how to generate less waste in the first place. In addition, under PAYT, everyone pays only for what they generate so they do not have to subsidize for their neighbour's wastefulness, as it happens in the fixed pricing systems. Thus, the findings support the design and implementation of the PAYT systems.

Towns and municipalities located in the western part of the state have lower air pollution concentration levels. In addition, when waste landfills are public or one of them is private, the air quality is improved. Studying the characteristics in specific municipalities, considering additional factors, such as the distance between municipality and the air monitoring station and meteorological data among others, these can be helpful in order to design the appropriate trash collection and recycling processes.

In this part some back of the envelope calculations are presented assuming that results imply causality. Lipfert et al. (2000) examined the effects of particulate matter on infant mortality using US data for 1990. More specifically, the elasticity of particulate matter with regard to infant mortality is 0.1181 for low birth weight (less than 2,500 kg) and 0.1217 for high birth weight (equal or more than 2,500 kg). Applying these estimates to our findings we find that the infant mortality would decreased by 0.0242 and 0.0256 per cent for low and high birth weight infants respectively if recycling rates increase by 1%. In other studies all-cause daily mortality is estimated to increase by 0.2-0.6% for a 10 $\mu g/m^3$increase in PM_{10} concentrations (WHO Regional Office for Europe, 2006; Samoli et al., 2008). Using these estimates the daily mortality is decreased by 0.0051-0.015% for a 1% increase in recycling rates. Other studies show that long-term exposure to $PM_{2.5}$ is associated with an increase in the long-term risk of cardiopulmonary and lung cancer mortality by 6-13% for a 10 $\mu g/m^3$ increase in $PM_{2.5}$ concentrations (Pope et al., 2002; Beelen et al., 2008; Krewski et al., 2009). Substituting in our estimates a 10% increase in recycling rates is associated with a decrease in the long-term risk of cardiopulmonary mortality by 1.26–2.74% per 10 $\mu g/m^3$.

6. Conclusions

This study examined the relationship between $PM_{2.5}$ air pollutant and recycling rate. A negative relationship between $PM_{2.5}$ and recycling rate has been found indicating that recycling can lead to air quality improvement. The reduction is 0.0017-0019 micrograms per cubic meter ($\mu g/m^3$) of $PM_{2.5}$ for a one percentage increase in recycling rates. Much of the energy and resources that are used to initially process a raw material only need to be used once when the raw materials are recycled, saving both energy and resources. In addition, many practices in USA and Europe include incineration processes. However, burning materials in order to generate electricity creates a demand for "waste" and discourages much needed efforts to conserve resources, reduce packaging and waste and encourage recycling. More than 90% of materials currently disposed in incinerators and landfills can be reused and recycled. Providing subsidies or incentives for incineration encourages local governments to destroy these materials, rather than investing on environmentally sound and energy conserving practices. In addition, increasing waste in landfills and incinerators pose considerable risk to the health and environment of neighbouring communities as well as that of the general population. Concluding, recycling can be an effective tool in the community for reducing waste generation, eliminating disposal and reducing air pollution. In addition, PAYT was found to be an important factor for air quality improvement. However, illegal dumping can be a disadvantage of PAYT. Thus, more attention should be paid on PAYT program, like the relation of its price with the fixed pricing system in the case where PAYT is absent. In parallel with the PAYT program and fixed pricing systems, the recycling prices and costs, trash delivery costs and generally the solid waste management expenditures can be examined.

It is suggested that the relationship between recycling rate and additional air pollutants, like SO_2, NO_X and CO_2 among others should be examined as the turning point may differ between pollutants. The reason is that the recycling process of each product is different and the air pollution for different pollutant might vary. In addition, whenever available, personal and household demographic and socio-economic characteristics can be considered for future research. In addition, the relationship between recycling and pollution can be examined also in line with, health effects including bronchitis, headaches, heart disease and cancer among others, health care costs, loss of productivity at work and human welfare impact.

Efforts should be prioritised by geographic area or resource, type of generator - residents, stores, industry- type of pollutant and cost to society. There should be state and federal identification, which supports and provides incentives for pollution prevention and recycling, considering also local legislation. A pollution prevention and recycling strategy, should be developed, which includes businesses, industries and governmental agencies in the community and establish targets for waste reduction which can be used by the private and public sector in the community.

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Appendix A

Massachusetts Department of Environmental Protection website (http://www.mass.gov/dep).

Massachusetts Department of Public Health (http://www.mass.gov/eohhs/gov/departments/dph/).

Massachusetts Executive Office for Administration and Finance(http://www.mass.gov/anf/research-and-tech).

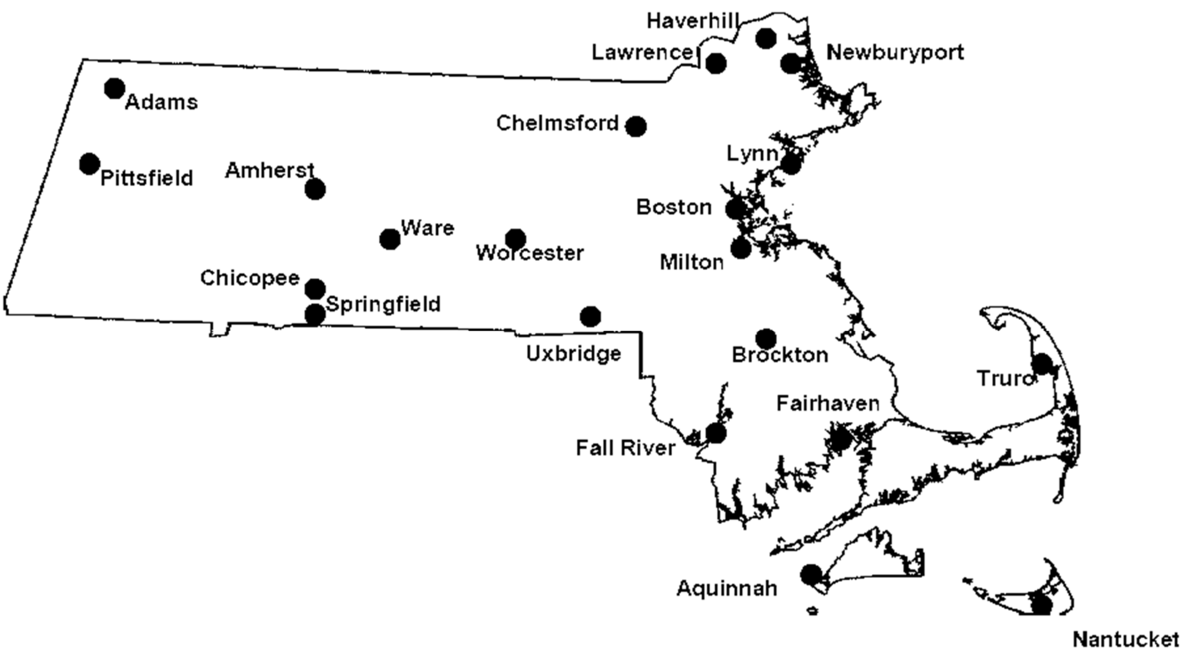
Massachusetts Department of Revenue (DOR) (http://www.mass.gov/dor/local-officials),

Massachusetts Executive Office of Labor and Workforce Development (http://www.mass.gov/lwd).

Tutiempo weather (http://www.tutiempo.net)

National ClimaticDataCenter (NCDC)(http://www.ncdc.noaa.gov).

Map 1. Massachusetts Air Monitoring Network for $PM_{2.5}$



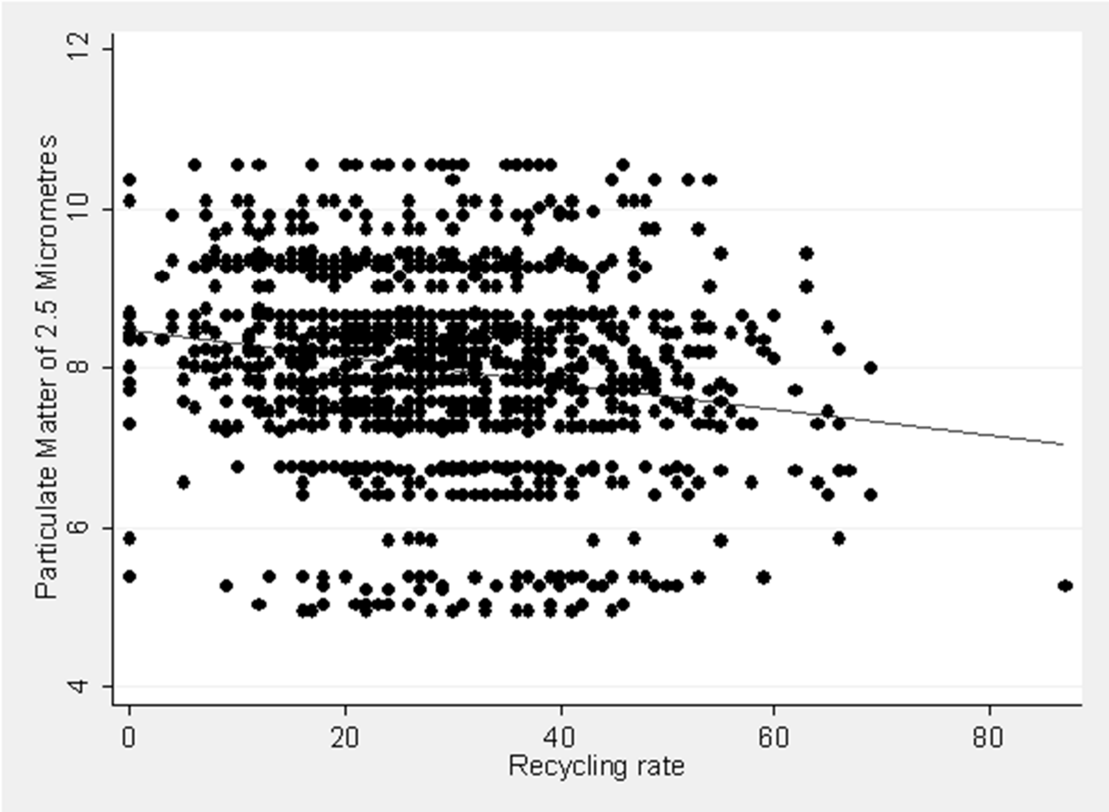
Source: Massachusetts Department of Environmental Protection website (http://www.mass.gov/dep).

Table 1. Summary Statistics

Variables		Period 2009-2012	Period 2009	Period 2010	Period 2011	Period 2012
$PM_{2.5}$($\mu g/m^3$)[1]	Mean	8.020	8.666	8.246	7.664	7.548
	Standard Deviation	0.611	0.608	0.621	0.618	0.580
Total Trash Tonnage	Mean	5930.131	5,023.165	6,196.451	6,544.734	6,385.21
	Standard Deviation	14,474.97	13,752.27	14,429.22	14,972.55	15,157.32
Recycling Rate	Mean	28.635	27.075	28.156	29.335	30.153
	Standard Deviation	6.257	6.882	6.704	5.949	6.297
Income Per Capita (2010 as baseline year)	Mean	35,347.43	32,465.55	35,391.79	36,210.97	37,344.69
	Standard Deviation	8,096.729	8,452.03	8,248.68	7,556.72	7,876.19
Unemployment Rate	Mean	7.238	7.827	8.057	7.079	6.588
	Standard Deviation	0.973	0.856	1.051	1.038	0.921
Average Temperature	Mean	12.082	9.043	13.901	14.638	10.700
	Standard Deviation	5.133	1.782	4.570	5.120	1.953
Precipitation	Mean	1,253.794	1,233.507	1,311.668	1,385.784	1,078.37
	Standard Deviation	190.605	97.681	166.563	115.894	205.823
Wind Speed	Mean	13.009	12.381	14.261	13.625	11.698
	Standard Deviation	3.496	2.864	3.541	4.096	2.670

$PM_{2.5}$ is measured in micrograms per cubic meter ($\mu g/m^3$), total trash tonnage in tonnes, temperature in fahrenheit, precipitation in inches per 24-hour, wind speed in miles per hour (mph).

Figure 1. Scatter Plot of Recycling Rates and $PM_{2.5}$



Map 2. Municipal Recycling Rates 2009

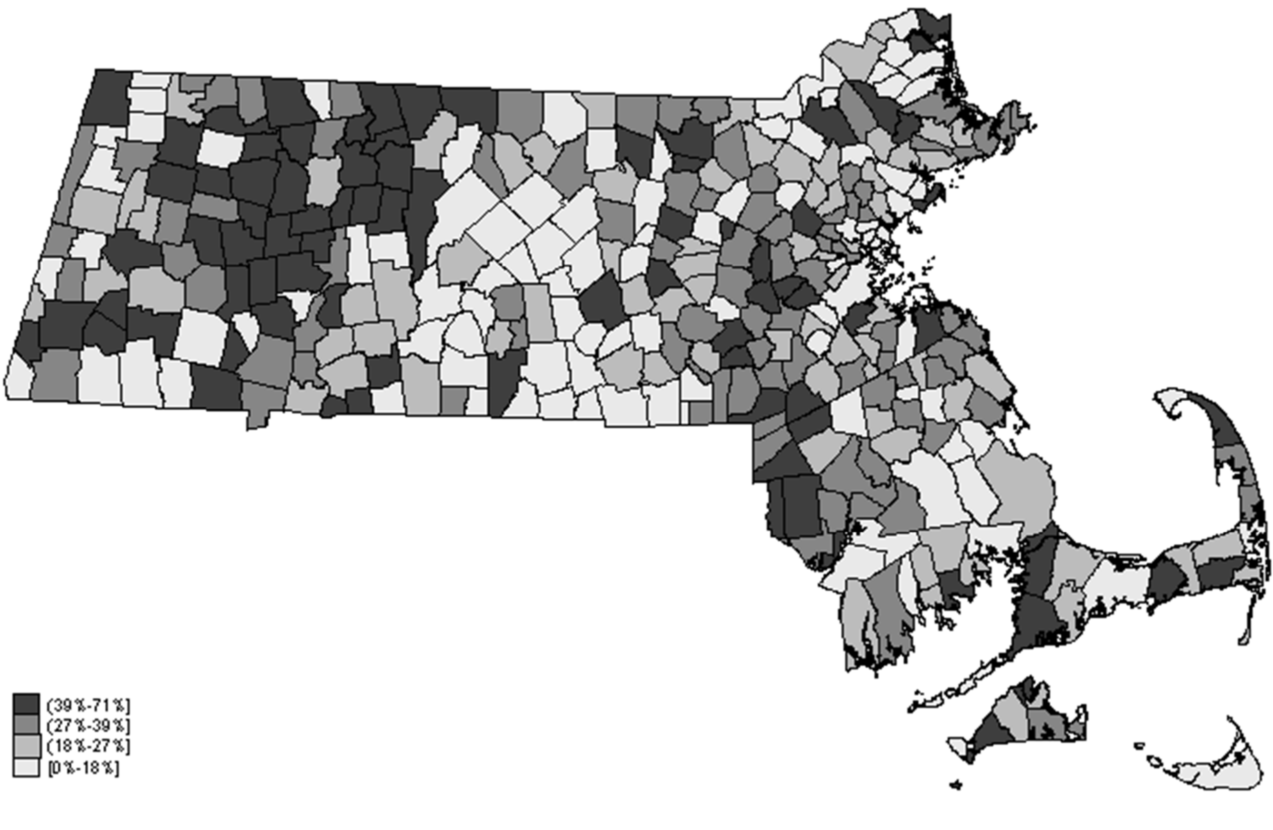


Table 2. Correlation Matrix

	$PM_{2.5}$	Total Trash Tonnage	Recycling Rate	Income Per Capita	Unemployment Rate
Total Trash Tonnage	0.0428 (0.3113)				
Recycling Rate	-0.1811 (0.0000)***	-0.1406 (0.0000)***			
Income Per Capita	-0.1195 (0.0000)***	-0.0697 (0.0299)**	0.2598 (0.0000)***		
Unemployment Rate	0.0785 (0.0054)***	0.0886 (0.0058)***	-0.1917 (0.0000)***	-0.4066 (0.0000)***	
Population Density	-0.0262 (0.3546)	0.5562 (0.0000)***	0.1722 (0.0000)***	-0.0697 (0.0129)**	0.0807 (0.0040)***

p-values in brackets, *** and ** denote significance at 1% and 5% level

Table 3. Regression Estimates of Equation (2) using Fixed Effects

Variables	**Fixed Effects Estimates**	**Fixed Effects Estimates†**
Constant	4.728 (1.892)**	5.431 (1.852)***
Recycling Rate	-0.0211 (0.0077)***	-0.0238 (0.0087)***
Total Trash Tonnage	0.0035 (0.0015)**	0.0042 (0.0018)**
Population Density	-0.0223 (0.0109)**	-0.0252 (0.0124)**
Income Per Capita	0.687 (0.328)**	0.986 (0.354)***
Income Per Capita Square	-0.0339 (0.0160)**	-0.0491 (0.0242)**
Unemployment Rate	-0.0807 (0.0328)**	-0.0993 (0.0337)***
Average Temperature	0.541 (0.193)***	0.751 (0.224)***
Minimum Temperature	-0.681 (0.204)***	-0.889 (0.234)***
Maximum Temperature	0.563 (0.230)**	0.806 (0.262)***
Precipitation	-0.194 (0.0287)***	-0.188 (0.0266)***
Wind Speed	-0.124 (0.0293)***	-0.138 (0.0685)**
PAYT		-0.0265 (0.0081)***
No. observations	1,274	1,116
R-square	0.2222	0.2866
Hausman test	112.75 [0.000]	103.85 [0.000]

Standard errors are between brackets, Standard errors clustered at municipality level
***, ** and * denote significance at 1%, 5% and 10% level.
The dependent variable is the logarithm of $PM_{2.5}$ and following variables are included as explanatory variables in the regression estimates: Combustion, Landfill, Municipality Type.
†Regressions include yard, food, trash waste services, reciprocal-regional program and PAYT

Chapter Four

Valuing Air Pollution in Britain Using Happiness and Life Satisfaction Data

Arnaud Chevalier♦ and Eleftherios Giovanis[*]

Abstract

This study explores the willingness to pay for (reducing) pollution in the UK. The Life Satisfaction Approach (LSA) is employed and the estimates are based on data from the British Household Panel Survey (BHPS). Using the respondents' residence postal codes allow us to map more precisely the air pollution to individuals' residence than other studies did before. In addition, the non-movers sample is considered in order to reduce endogeneity. The effects of air pollution on individuals' happiness are estimated and their monetary value is calculated. In particular, four air pollutants are examined; sulphur dioxide (SO_2), ground-level ozone (O_3), nitrogen dioxides (NO_X) and carbon monoxide (CO). Moreover, three different estimation approaches are followed. The first relies on panel fixed effects regressions. The second introduces dynamics. The third approach is the latent class ordered probit. The results show that the O_3 presents the strongest negative effects on happiness followed by SO_2, CO and NO_X. The annual monetary values for ground level ozone range between £588-£864 for a drop of one standard deviation, while the respective values for the other air pollutants range between £288-£696. The estimates are dependent on the estimation approach and dynamic panel model leads to the highest estimates.

Keywords: Air pollution, Environmental valuation, Happiness, Life satisfaction approach, Subjective well-being

JEL codes: I31, Q51, Q53, Q54

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[8]University of Essex. Institute for Social and Economic Research, *British Household Panel Survey, Waves 1-18, 1991-2009: Secure Data Service Access, National Grid Reference (Easting, Northing, OSGRDIND)* [computer file]. *2nd Edition.* Colchester, Essex: UK Data Archive [distributor], August 2010. SN: 6340.

1. Introduction

Air pollution leads to worst health outcomes (Currie and Neidell, 2005) and increased death probability (Janke et al., 2009). However, policies to reduce pollution are often hardly fought on the ground of their high financial costs. It is thus crucial to have reliable estimates of the public willingness to pay for a cleaner environment. Economists have long worried about valuing the environment (see Leontief, 1970 for an early example). The difficulty in doing so steams from the absence of markets pricing the environment/pollution. The contribution of this study is that the analysis relies on detailed micro-level data, using BHPS' respondents' post codes expressed on grid references coordinates. This allows us to map air pollution to individuals residence far more accurately, instead of using electoral divisions or counties like other studies do (Ferreira et al., 2006; Luechinger, 2010). Secondly, the population interest is limited to non-movers sample in order to reduce the endogeneity as it is discussed in more details in the methodology part. In addition, this is the first study presenting three different panel estimates to deal with the potential endogeneity of the pollution measure. Initially, an individual level fixed effect model is applied, we then estimate a dynamic panel model before estimating a latent class ordered probit model. There are several key advantages of using these estimators. Firstly it is possible to control for the local authority district-specific, time invariant characteristics. The dynamic models allow controlling for time varying unobservables. Finally, estimating a latent class ordered probit also model the heterogeneity of the pollution effect.

To value the environment, two popular methods exist: revealed preference and stated preference. Revealed preference relies on hedonic price analysis, i.e. uses variations in house price to elucidate the price attached to a cleaner environment. The stated preference approach is based on contingent valuation in surveys, and attempt to directly elucidate the environmental value from question (Carson et al. 2003). Both methods may lead to biased estimates. Hedonic price analysis requires the market of interest (typically the housing market) to be in equilibrium at even small geographical level (Frey et al., 2009), the experience of consuming the common good of interest, here pollution, is perceptible (Rabin, 1998) and migration is costless (Bayer et al., 2009). These hypotheses are unlikely to be satisfied, making this evaluation approach problematic. In stated preference analysis, the hypothetical nature of the surveys and the lack of financial implications may lead to superficial answers (Kahneman et al., 1999).

Instead this paper relies on life satisfaction evaluation (LSE). One advantage of this method is that it does not rely on asking people how they value environmental conditions or on equilibrium in the housing market. Instead individuals are asked to evaluate their general life satisfaction controlling for pollution and income. Then, the estimated effects of pollution and income on life satisfaction are equivalised to calculate a willingness to pay for pollution (see Clark and Oswald, 1996, for an early application). The LSE approach does not require awareness of causal relationships- but simply assumes that pollution leads to change in life satisfaction. These changes can be driven by observed or unobserved pollution variation. LSE is thus closely related to hedonic pricing but relies on life satisfaction rather than house price to evaluate how individuals value their environment, and thus requires less stringent assumption. More precisely, LSE does not rely on the ability of the respondents to account and consider all the relevant consequences of a change in the provision of a public good. In fact the respondents might not even notice that there is a relationship between environmental conditions and their subjective well-being. Obviously, satisfaction level may be correlated with some unobserved amenities that also affect pollution level, and in cross section, the LSE may thus be biased. Instead, we rely on individual level panel data, so that unobserved individual level and geographical characteristics can be accounted for. The identification then comes from variation in pollution level between interviews.

LSE approach however has weaknesses and limitations. While there is growing evidence to support the suitability of individual's responses to life satisfaction for the purpose of estimating non-market values (Frey et al., 2009), some potential limitations remain. Most importantly, self-reported life satisfaction must be regarded as a good proxy for an individual's utility (Frey et al., 2009; Levinson, 2012). Furthermore, in order to yield reliable non-market valuation estimates, life satisfaction measures must reflect not only stable inner states of respondents, but also current affects and to be comparable across groups of individuals under different circumstances (Luechinger and Raschky, 2009).

Similar to the limitation of the hedonic property pricing method, the drawback of LSA is the sorting problem, where it is possible that people choose where they reside. This would bias the air pollution variable's coefficient- and therefore the monetary value- downwards as those least resilient to air pollution would choose to reside in areas with cleaner air. Nevertheless, both non-movers and movers sample are examined in order to reduce endogeneity. Therefore, the population of interest in estimates, including robustness checks, is limited to non-movers, similarly to the study by Luechinger (2009), who excludes the individuals moving across county boundaries, thus county specific effects are absorbed by the individual specific fixed effects. However, this study uses a more detailed geographical dataset based on the individual's residence grid reference and controlling for local authority districts effects. In addition some authors argue that the life satisfaction approach values only the residual benefits or costs of the non-market good not captured in housing markets (Luechinger, 2009; van Praag and Baarsma, 2005). In that case, Ferreira and Moro (2010) suggest that the relationship depends on whether the hedonic markets are in equilibrium or not, as well as on the econometric specification of the life satisfaction function.

Moreover, the air pollution is based on dates around the interview making it more exogenous and avoiding the above-mentioned sorting problem. However, another limitation is that individuals located in polluted areas might be less sensitive to pollution because they become habituated to the poor air quality or they sort into polluted areas in the first place because they are less concerned about air quality (Luechinger, 2009; Levinson, 2012). Nevertheless, robustness checks between individuals located in high and low polluted areas are conducted. Moreover, people might sort into polluted areas not because are less concerned, but because there might be more opportunities make them happier such as labour market choices. Usually cities are more polluted because of the traffic, but living in cities permits the advantages of the opportunities of proximity, diversity and marketplace competition, where money, services, wealth, health and other opportunities are centralized. Another limitation of LSE approach is the functional form of income and its consequences in monetary valuation. However, this study examines also quadratic terms on income in the robustness checks part.

An additional important drawback of the LSE approach that it should be considered is the estimation of the income coefficient and the possible degree of reverse causality. More specifically, Pischke (2011) finds evidence to suggest that the direction of the income-life satisfaction relationship is mostly causal, however he states that there is some degree of reverse causality, that people who are more satisfied with their lives might earn more. For example Powdthavee (2010) found that extraverted people are more likely to report higher levels of life satisfaction and thus to be more productive in the labour market. A solution for this issue is to include an instrumental variable for income in life satisfaction regressions (Luechinger, 2009; Ferreira and Moro, 2010).

However, Stutzer and Frey (2012) suggest that instrumental variable approaches are difficult to convince. This is due the fact that it is almost impossible to find an appropriate instrumental variable given that almost any factor can be considered to determine an individual's life satisfaction. In addition, Pischke and Schwandt (2012) conclude that industry wage differentials are not useful instruments for income, even when the instrumental variable regressions pass some specification tests.

Another issue which rises using the LSE is that when income is included as an explanatory variable in life satisfaction regressions, small estimated income coefficients are common which in turn lead to high monetary values. This is due the fact that individuals compare current income with past situations and/or the income of their peers; thus both relative and absolute income matter (Ferrer-i-Carbonell, 2005; Clark et al., 2008; Mentzakis and Moro, 2009; Ferreira and Moro, 2010; Levinson, 2012). A rise or decline in individual income will produce increases or decreases in happiness. However, if habituation to income occurs very rapidly, then only very recent changes in income will have an effect.

Four major air pollutants are investigated, sulphur dioxide (SO_2) ozone (O_3), nitrogen oxides (NO_X) and carbon monoxide (CO), as these pollutants are considered the most dangerous[9].From our favoured estimates, the annual monetary values for a one standard deviation change in SO_2 range from £300 to £660; for O_3, NO_x and CO the range of monetary values are £588-£864, £288-£696 and £396-£492 respectively.

The paper is organized as follows. Section 2 presents a short literature review. Section 3 describes the methodological framework. In section 4 the data and the research sample design are provided. In section 5 the results of estimating several versions of a happiness function, with air pollution included, are reported, as well as,

[9] Department for Environment, Food and Rural Affairs (DEFRA), The Air Quality Strategy for England, Scotland, Wales and Northern Ireland, 2007.

the effects of air pollution on happiness and their monetary value are presented and discussed. In section 6 the concluding remarks are presented.

2. Literature review

This section presents the previous literature review on traditional valuation methods, such as the revealed and stated preference methods and discussing on the latest developments on hedonic pricing methods, life satisfaction approach, as well as on choice modeling. Next the MWTP values found in the previous researches are compared with those derived from the current study.

Initially, previous researches on revealed preference methods are discussed. Under the assumption of perfectly competitive housing market, a change in any environmental characteristics is reflected by a change in market price, and reflects the buyers' marginal willingness to pay for this characteristic; see Rosen (1974) for details on hedonic pricing. Rosen (1974) presented an integrated treatment of hedonic theory and the demand for and supply of differentiated products. He also outlined an econometric procedure for estimating the demand and supply functions that determine the hedonic price function. Ridker and Henning (1967) completed the first application of hedonic pricing to estimate the effect of air pollution on property values in St. Louis, Missouri. They estimated that a 1 standard deviation change in sulfate was associated with a change in 2.8% in the values of residential properties. Numerous studied followed the same methodology and are reviewed in Smith and Huang's (1995) meta-analysis. Smith and Huang (1995) concluded that estimates of the willingness to pay for a 1 unit drop in total suspended particulate (TSP) range from 0 to \$100 (at 1984 value). However, Bayer et al. (2009) show that when moving is costly, estimates relying on hedonic valuation of the housing market are biased downwards. Moreover, naïve estimates omit that both local air quality and market value are likely to be correlated with unobserved local economic factor, which biases the estimates downwards. Using instrumental variable (distant emissions), they estimate that the MWTP for a one unit drop in TSP is $114 (at 1984 value). However, using a regression discontinuity approach, Greenstone and Gallagher (2008) estimate that the willingness to pay for a cleaner environment in the most polluted hazardous waste site is nil. Kuminoff et al. (2010) suggest that accuracy in estimates can be increased by moving from the standard linear specifications for the price function to a more flexible framework using a combination of spatial fixed effects, quasi-experimental identification, and temporal controls for housing market adjustment.

However there are issues with hedonic pricing methods. More specifically, the weak results may be explained by two econometric identification problems. Firstly, it is likely that the estimated association between housing price and air pollution is biased due to omitted variables. Secondly, if there is heterogeneity across individuals in preferences for clean air, then individuals may self-select into locations based on these unobserved differences (Chay and Greenstone, 2005). Additionally, this approach is subject to market distortionbecause MWTP is a crude average of the marginal values estimated under specific circumstances, as it relies on an equilibrium assumption (Smith and Huang, 1995; Frey et al., 2009). Indeed the depth of the housing market may well be correlated with pollution, leading to selection bias in hedonic pricing analysis.

In the literature three main sorting and hedonic pricing models have additionally been developed; the Calibrated Sorting (CS), the Random Utility Sorting (RU) and the Pure Characteristics (PC) sorting models. These models differ on how they: (a) define the set of choices faced by each household; (b) specify the shape of the preference function; and (c) develop instruments to control for endogenous amenities (Bayer and

Timmins, 2005; 2007; Kuminoff et al., 2013). Regarding pint a) the choice set the advantage of the RU and CS models is that they facilitate describing the choice of a house as being related to choices in other markets. Bayer et al. (2004) argue that the RU model is the only one where the connection between housing and labour market choices is acknowledged. However, their random utility model lacks a budget constraint (Bayer et al., 2004).

Regarding preferences in the PC specification, every household is required to have the same relative preferences for every amenity, observed and unobserved, while the CS specification relaxes this depiction of preference heterogeneity by allowing households to differ in their relative preferences. PC model is characterized by the vertically differentiated case, which is the case when households agree on the ranking of communities by overall amenity provision, they must also agree on the opportunities for spatial substitution. On the other hand CS and RU models, which are characterized by horizontal differentiation, allow more diversity in substitution possibilities. However, the vertical/horizontal modeling choice can be viewed as offering a bias/variance tradeoff. More specifically, vertical differentiation would bias the PC estimator for preferences and therefore the conclusions that would be drawn about welfare measures. On the contrary, horizontal differentiation eliminates the restriction that causes bias, but the added dimensionality of preferences increases the scope for untested distributional assumptions to drive the estimates (Kuminoff et al., 2013).

Concerning the instrumental variable approach, the advantage of the production function approach to addressing endogenous amenities in the CS model, illustrated by Ferreyra (2007) and Calabrese et al. (2007), is that it does not require any assumption about the relative importance of unobserved amenities. PC develops instruments based on functions of the community income rank, and RU sorting model develops instruments based on functions of the exogenous attributes of substitute locations.

However, CS presents a trade-off because the production function approach accepts, as a maintained condition, a specific form for the amenity's production function. Thus this approach ties the consistency of the estimator to the specification for the amenity production function. On the other hand the instrumental variables approaches used by PC and RU are consistent as long as the instruments are valid (Kuminoff et al., 2013).

Next the previous research studies using stated preference methods are discussed. Contingent evaluation studies are difficult to compare since each design is usually unique and includes "(1) a description of the commodity to be valued; (2) a method by which payment is to be made; and (3) a method of eliciting values" (Croper and Oates, 1992, 710). Loehman and De (1982) estimated the yearly WTP for a one-day per year reduction in severe cough, severe shortness of breath, and minor eye irritation to be between US$7 and US$46. Hall et al. (1992) using contingent valuation obtained a willingness to pay of US$23 per day, at 1990 prices, for a one-day-per-year reduction in minor restricted-activity. Loehman et al. (1985) asked respondents whether or not they would vote to improve air quality by 30 percent, along with associated health and visibility benefits, at various costs, and showed them photographs of the sky with clean and dirty air. The average annual willingness to pay was $980 in Los Angeles and $251 in San Francisco, in 2008 dollars. Loehman et al. (1994) using a survey estimated two different types of willingness to pay responses -willingness to pay to avoid loss of air quality and willingness to pay to obtain gains in air quality, so as to explore possible asymmetry in the pollution effect. The survey took place in the spring of 1980 in the San Francisco Bay area and it encompassed 946 census tracts and 73 cities. The estimated MWTP for increases in health was \$13 per month at 1980 prices while the MWTP to avoid losses was \$8 per month. Hammitt and Zhou (2006) valued colds, chronic bronchitis and mortality related to air pollution in China using a three-location Contingency Valuation (CV) survey for the general population. They asked people's MWTP for health risk reductions. They interviewed about 3,700 people in surveys conducted in June and July of 1999 in Beijing and Anqing. They examined the indoor air pollutants PM_{10} and SO_2 and estimated that the statistical cost of a cold ranged between \$3 and \$6, the value of a statistical case of chronic bronchitis ranged between \$500 and \$1,000, and the value per statistical life ranged between \$4,200 and \$16,900 in 2000 dollars. Generally, the majority of the studies find a negative and significant association between air pollution, house prices and health.

Concerning the contingent valuation approach there are also some criticisms. One argument is that individuals do not have adequate understanding of what they are being asked to evaluate. Another disadvantage is that the individuals might have limited or poor incentives to disclose their true demand (Luechinger, 2009; Frey et al., 2009; MacKerron and Mourato, 2009). In addition the answers may depend substantially on the form in which questions are posed. Direct questioning or contingent valuation studies ask respondents to value an output, such as a day spent in an activity, rather than a change in pollution concentrations per se (Croper and Oates, 1992). Also if the commodity to be valued is not well understood, contingent valuation responses are likely to be unreliable. More specifically, responses tend to exhibit wide variation, and respondents may even prefer less of a good to more, especially when there are open-ended questions for a good which is not traded in conventional markets (Croper and Oates, 1992).

However, other studies examine choice modeling (CM) or choice experiments (CEs) and it is claimed that may be more appropriate than contingent valuation to elicit WTP (Hanley et al. 2001a; Campbell, 2007; Campbell, et al. 2008). These experiments include survey-based methodologies for modeling preferences for goods, where goods are described in terms of theirs attributes and the levels that these take. Various preference series with alternatives, differing in terms and levels, are presented to the respondents, who are asked the most preferred or to rank the various alternatives. Then by including price or cost as one of the attributes of the goods, the WTP can be indirectly recovered by the respondent's rankings or choices (Hanley et al. 2001a; Campbell, et al. 2011). CE is more suitable in measuring the marginal value of changes in various characteristics of environmental programmes. In addition, CE is more informative than the discrete choice CV studies as respondents have many options to express their preference for a good over given a range of payment amounts. Finally, as it was mentioned previously, CE relies on ratings rankings or choices of the respondents amongst a series of alternative package of characteristics from where the WTP can be indirectly calculated. In this way CE may minimise the response difficulties found in CV such as strategic behaviour (Hanley et al. 2001a; Campbell, et al. 2011).

However, CEs have also weakness. Firstly, the repeated answers per respondent pose statistical problems and the correlation between responses should be taken into account (Adamowicz et al, 1998). In addition, CE modeling is sensitive to study design, where the choice of the levels chosen to represent them and the way that the respondents receive them are neutral or not. This implies that there might be an impact on the marginal utilities values (Hanley et al., 2001a). Hanley et al. (2001b) found that changing the number of choice tasks, respondents produced significant impacts on the model of preferences derived from their responses.

In addition, other studies use *ad hoc* surveys. Alberini (1995) looked at designs that are constructed *ad hoc* and the variance of the estimates is used as the criterion for comparing the estimates from the alternative designs, as well as for the estimates of alternative statistics including mean and median WTP. Alberini (1995) found the optimal designs for a single-bound study, which is a survey in which only on payment question is available to each respondent. Hanemann (1984) argues that economic theory is useful to guide variable selection and, in particular, functional-form specification. On the other hand, *ad hoc* is based on intuitive specifications of a functional form. Empirically, Boyle and Bishop (1988) found that specifications are consistent with utility theory, while functional forms derived from economic theory may not provide statistically significant estimates of coefficients, and some coefficients may have the wrong signs. In contrast, an *ad hoc* specification used by Boyle et al. (1988) did yield statistically significant coefficients with signs meeting a priori expectations in the Boyle and Bishop's (1988) study. However, Carson and Hanemann (2005) argue that using an extra piece of information and additional function forms would be acceptable if there is a strong theoretical or practical basis for this or if empirically its introduction in a model resulted in small changes in the estimate of mean WTP and moderate increases in its confidence interval. However, the results, derived from models using *ad hoc* specification, tend to be very sensitive to specific assumptions employed.

To alleviate the dependence on the housing market and to evaluate the willingness to pay, researchers have also used life satisfaction. By regressing life satisfaction on pollution[10], income and control variables, it is possible to infer the marginal willingness to pay for pollution (i.e the income change that has the same effect on life satisfaction as the pollution change). Applications of this method includes Welsch (2002; 2006; 2007), who examines average life satisfaction in relation to average air pollution values across

[10]There is the general belief that data on subjective well-being are valid and can be informative (Di Tella et al., 2003; Pischke, 2011).

countries and finds significant negative associations in each case. More specifically, Welsch (2002) used cross section data from 54 countries in 1990 and 1995. The dependent variable is the country average happiness. MWTP is found to be $126 for a one μg/m^3 decrease in NO_2. Welsch (2006) used the Eurobarometer, a series of cross-section during the period 1990-1997 for 10 European countries. The dependent variable is country-year average of life satisfaction and the air pollutants examined are the Lead (Pb) and NO_2. Welsch (2006) found a MWTP equal to $184 for a one μg/m^3 decrease in Pb and $519 for NO_2. Di Tella and MacCulloch (2007) valued the MWTP at $171 for sulphur oxides ($SO_X$) in the OECD countries. However, these studies are likely to be biased by measurement error due to the aggregation of pollution to national level.

To reduce this aggregation problem, Ferreira et al. (2006), examined individual-level data on life satisfaction matched to local level data on air pollution and other environmental quality parameters from a 2001 representative sample of 1,500 men and women living in Ireland. Using cross sectional data, they find negative associations between air pollutions and life satisfaction estimating that the average individual is willing to pay 1,100 euros for a one microgram per cubic meter decrease in PM_{10}. Levinson (2012) used data from the General Social Survey (GSS) which is a general survey on demographic characteristics and attitudes of residents of USA, during period 1973-1996. Levinson (2012) finds that a one μg/m^3 increase in PM_{10} reduces an average person's stated happiness by the equivalent of $464. MacKerron and Mourato (2009) using a survey of 400 respondents in London in 2007 examined the effects of NO_2 on life satisfaction and found that a 1% increase in NO_2 levels is equivalent, in life satisfaction terms, to a 5.3% drop in income or $2,340. Rehdanz and Maddison (2008) report that the perceived levels of air pollution are also negatively related to life satisfaction scores in Germany. Ferreira and Moro (2010) using a detailed micro-level data, derived from the Urban Institute Ireland National Survey on Quality of Life conducted in 2001, found that the marginal willingness to pay for a reduction of one microgram per cubic meter of PM_{10} is 945 euros.

However, studies, such as those by Ferreira et al. (2006) and MacKerron and Mourato (2009) rely on cross sectional and do not account for the endogeneity of pollution; i.e. areas with high pollution levels are likely to also have some other amenities that negatively affect life satisfaction. It is thus important to account for the possible simultaneity of changes in pollution level and life satisfaction due to local employment for example.

The most relevant paper to our study is by Luechinger (2009) who also uses an individual level panel data (the German Socio-Economic Panel (GSOEP). The pollution data is available for about 450 German counties over the period 1985-2003. Luechinger (2009) argues that the pattern and evolution of SO_2 pollution points at the potential simultaneity of local economic activity and pollution. The instrument used is the mandated installation of scrubbers at power plants. The MWTP is \$183 for sulphur dioxide (SO_2), which becomes larger (\$313) when instrumental variable estimates are considered. Therefore Luechinger (2009) claims that failure to control for this simultaneity biases the pollution coefficients in the life satisfaction regressions towards zero. More recently, Ferreira et al. (2013) examined the effects of SO_2 in life satisfaction in Europe using the European Social Survey. Their findings show that an increase of 1 $\mu g/m^3$ in SO_2 concentrations is associated with a reduction in life satisfaction of 0.016 points on the life satisfaction scale, from 0- 10. Luechinger (2010) examined 13 European countries during period 1979-1994 and found that MWTP is valued at \$154 for sulphur dioxide (SO_2). However, using IV estimates the MWTP becomes \$344. In order to address the endogeneity problem, Luechinger (2010) instrument a country's air pollution with the long-range trans-boundary air pollution caused by emissions in foreign countries. Foreign emissions are assumed to be uncorrelated with domestic economic activity; this might be however questionable.

Generally, LSE also has its weaknesses and limitations as they have been presented and discussed in the introduction part. Moreover, a problem common to all methods is that consumption and relocation decisions are based on perceived rather than objective amenity levels. More specifically, in case people's perceptions and objective measures do not correspond sufficiently, the estimates may be severely biased. However, in contrast to the revealed preference methods, the LSE might capture indirect effects of externalities on individuals' utility through effects on health, even if there are no direct effects. Table 1 presents the summary for these studies, along with our results, and the estimated MWTP values are provided with reference to year 2012.

Finally, this study follows the recent literature and explores what happens if the effects of air pollution and income varied in different parts of the life satisfaction distribution. To the best of our knowledge, empirical evidence on the heterogeneous effect of air pollution on different parts of the life satisfaction distribution is scarce, and such evidence is virtually non-existent. For this reason, this study paper aims to fill this gap in the literature.

3. Methodology

3.1 Panel regressions

Happiness and life satisfaction can serve as an empirically valid and adequate approximation of individual welfare, in a way to evaluate directly public goods (Frey et al., 2009).

One difficulty with life satisfaction measures is that they are self-assessed on an arbitrary scale and can thus suffer from differential item functioning (DIF), making the assumption of interpersonal comparisons potentially difficult (see Kapteyn et al., 2010 for a discussion). However, this research relies on inter-temporal comparisons of utility within individuals and we assume that the scale and the interpretation of the question by a respondent remains the same between survey waves, which reduces the potential bias associated with DIF. As such, we estimate the following model of life satisfaction (LS) for individual *i*, in area *j*, at time *t.*

$$LS_{i,j,t} = \beta_0 + \beta_1 e_{j,t} + \beta_2 \log(y_{i,t}) + \beta_3 D_{i,j,t} + \beta' z_{i,j,t} + \gamma W_{j,t} + \mu_i + l_j + \theta_t + l_j T + \varepsilon_{i,j,t} \quad (1)$$

The vector $e_{j,t}$ is the measured air pollution in location *j* and in time *t*.$log(y_{i,t})$ denotes the logarithm of personal or household income, $D_{i,j,t}$ is the distance variable between the respondent's and air monitoring location and *z* is a vector of household and demographic factors, discussed in the next section. *W* is a vector of meteorological variables, in location *j* in time *t*.μ_i denotes the individual-fixed effects[11],l_j is a location (local authority) fixed effects, θ_t is a time-specific vector of indicators for the day and month the interview took place and the survey wave, while l_jT is a set of area-specific linear time trend, which controls for unobservable, time-varying characteristics in the area. Finally, $e_{i,j,t}$ expresses the error term which we assume to be *iid*. Standard errors are clustered at the wave specific local authority level.

The marginal willingness-to-pay (MWTP) can be derived from differentiating (1) and setting dLS=0. This is the income drop that would lead to the same reduction in life satisfaction than an increase in pollution. Thus, the MWTP can be computed as:

$$MWTP = -\frac{dy}{de} = -\frac{\partial f}{\partial e} / \frac{\partial f}{\partial y} \quad (2)$$

[11]Based on a Hausman test, a fixed effect model is preferred to a random effect model.

As mentioned above, the model is identified from changes in the pollution level within individuals between interviews rather than between individuals. To limit endogeneity issue we limit the population of interest to non-movers, since the decision to move may well be correlated to pollution level. The panel data analysis applied will eliminate the area fixed effects for non-movers, while for movers the error term contains the difference in the area fixed effects of the two locations, which may be correlated with the difference in air pollution levels across the two locations.

The fraction of non-movers, which includes the individuals up to their first move, is 83.50 per cent. The issue of the selection bias regarding the air pollution and whether it is randomly assigned to non-movers is discussed in the data section, where the summary statistics are reported. In addition, a regression analysis is presented to examine the selection bias. More specifically, this bias will materialise only if the decision to move to a new area in period t is affected by the air pollution in the previous residence area in period $t-1$. Therefore, if moving decisions are affected by past air pollution levels, individuals who did not move in response to a given realization of pollution must have received shocks to their moving decision different from those received by those who moved somewhere else. If shocks to life satisfaction and to moving decisions are correlated, this will potentially bias the estimates.

We argue that variation in pollution level between interviews is possibly exogenous and driven by differences in the time of the year that the interviews take place, as well as by the variation in the level of pollution between years due to variations in economic activity, weather conditions or other shocks. Evidence of these exogenous changes is provided in the data section. Of course, time of interview, unemployment rate at local authority district level and weather may have a direct effect on self-reported life satisfaction, it is thus important to directly control for these variables. We also note that there has been a general reduction of pollution over time, but that this may differ by region and as such it is of prime importance to control for area specific trends.

In its current form the model cannot be estimated by ordered probit or logit using fixed effects. With cross-section data, these parametric models are very easy to use and to estimate by maximum likelihood. However, extensions to a panel data context are complex and far from obvious. Unlike in the linear model, no simple transformation - such as first-differencing or within-transformation- is available that would purge the ordered response models from the individual-specific fixed effects. Therefore there are two options, either estimating the model considering the dependent variable as continuous or converting the dependent ordinal variable in continuous variable assigning z-scores. The second procedure is followed and it was introduced by van Praag and Ferrer-i-Carbonell (2004).To compute probit OLS, the categorical dependent variable is rescaled by deriving *Z*-values of the standard normal distribution that correspond to cumulative frequencies of the original categories. More specifically the probit OLS uses a transformation such that the new dependent variable takes the conditional mean-given the original ordinal rating- of a standardised normally-distributed continuous variable, calculated based on the frequencies of the ordinal ratings in the sample (see Cornelissen, 2006, for an example). The advantages of this are that it is quicker to compute than the ordered models, and there is the possibility of applying panel data methods, such as individual fixed effects. The calculation of the dependent ordinal variable can be stated as:

$$LS_{i,j,t} = E(Z \mid \mu_1 < Z < \mu_2) = [\phi(\mu_1) - \phi(\mu_2)]/[\Phi(\mu_2) - \Phi(\mu_1)] \qquad (3)$$

Z is a standard normal random variable, φ is the standard normal probability density function, and Φ is the standard normal cumulative density function. Generally, OLS and Probit-OLS have been found to provide comparable estimates (Van Praag and Ferrer-i-Carbonell. 2006; Luechinger, 2009, 2010; Stevenson and Wolfers, 2008; Wunder and Schwarze, 2010). We confirm this findings as results from Probit–OLS and OLS are very similar and the latter are not presented.

3.2 Dynamic panel regressions

The static model (1) faces some issues. Firstly, because causality may run in both directions, from pollution to happiness and vice versa – the regressors may be correlated with the error term. Furthermore, time-invariant fixed effects personal, demographic and geographical characteristics, like local authority districts, may be correlated with the explanatory variables. To further account for potential endogeneity of the pollution variable we also estimate dynamic panel models whereby we introduced lagged dependent variable. This is the case because the dynamic panel data model allows us to determine the timing and duration of impact of air pollution on well-being, and to account for dynamic trends in air pollution, while controlling for local authority-specific unobservables. The model is then defined as:

$$LS_{i,j,t} = \beta_0 + \beta_1 LS_{i,j,t-1} + \beta_2 e_{j,t} + \beta_3 \log(y_{i,t}) + \beta_4 D_{i,j,t} + \beta z_{i,j,t} + \gamma W_{k,t} + \mu_i + l_j + \theta_t + l_j T + \varepsilon_{i,j,t} \quad (4)$$

However, model (4) has some drawbacks. One issue is the fact that including the lagged dependent variable $LS_{i,j,t-1}$ gives rise to autocorrelation (Nickell, 1981).We solve the autocorrelation problem by estimating a dynamic panel version of (4) using the

Arellano–Bond estimator which accounts for reverse causality. It estimates the parameters of the system by specifying the model in first differences and uses lagged levels of the endogenous variables as instruments (Holtz-Eakinet al*.,* 1988; Arellano and Bond, 1991). These estimators, unlike OLS and conventional FE and RE estimation, do not require distributional assumptions, like normality, and can allow for heteroscedasticity of unknown form (Greene, 2011). Furthermore, the difference GMM uses first-differences on both sides of equation (4) -which drops out the time invariant factors and individual-specific unobservables and then estimate the following model:

$$\Delta LS_{i,j,t} = \beta_1 \Delta e_{j,t} + \beta_2 \Delta \log(y_{i,t}) + \beta_3 \Delta LS_{i,j,t-1} + \beta' \Delta z_{i,j,t} + \Delta u_{i,j,t} \quad (5)$$

$\Delta LS_{i,j,t}=(LS_{i,j,t} - LS_{i,j,t-1})$, $\Delta LS_{i,j,t-1}=(LS_{i,j,t-1} - LS_{i,j,t-2})$, $\Delta e_{j,t}=(e_{j,t}- \varepsilon_{j,t-1})$,

$\Delta log(y)_{j,t}=(log(y)_{j,t}- log(y)_{j,t-1})$, $\Delta z_{i,j,t}=(z_{i,j,t}- z_{i,j,t-1})$ and $\Delta u_{i,j,t}=(u_{i,j,t}- u_{i,j,t-1})$. Since $LS_{i,j,t-2}$ is correlated with the first differenced lagged dependent variable, but uncorrelated with the first difference of the errors, i.e. E($LS_{i,j,t-2}{'}(LS_{i,j,t-1} - LS_{i,j,t-2})$) ≠0 and E($LS_{i,j,t-2}{'}(u_{i,j,t-1} - u_{i,j,t-2})$) = 0, then $LS_{i,j,t-2}$ can be used as an instrument for $(LS_{i,j,t-1} - LS_{i,j,t-2})$.

Therefore, by first differencing the regressors the local authority-specific fixed effect is removed, because it does not vary with time solving this way the correlation problem of local authority districts with the explanatory variables. Additionally, the first-differenced lagged dependent variable $LS_{i,j,t-1}$ is also instrumented with its past levels accounting this way for the autocorrelation problem. The Arellano-Bond estimator was designed for small *T* and large *N* panels.

However, using the GMM framework an important issue rises. As it was mentioned previously, there is a degree of reverse causality between life satisfaction and income (Powdthavee, 2009; 2010; Stutzer and Frey, 2012; Pischke and Schwandt, 2012). GMM is preferred to 2SLS because the latter is inefficient in the general over-identified case with heteroskedasticity and when there is serial correlation in the error terms. However, the exclusion restriction is hardly satisfied because happiness depends on past income and other past living conditions, even if the regressions pass the specification tests.

On the other hand is possible that the exclusion restriction is satisfied based on the non-adaptation to income hypothesis. More specifically, Di Tella et al. (2010) found that the coefficients on the lags of income sum to −0.15 rejecting the hypothesis that there is no adaptation to income. In terms of size they indicate that after four years the impact of income falls from 0.23, which is derived by the 1st or the current year income coefficient, to 0.08 expressed by the lagged income of order four. These adaptation effects are consistent with the model of Pollak (1970) and Wathieu (2004). For example the study by Brickman et al. (1978), showed that individuals who had won between \$50,000 and \$1,000,000 at the lottery the previous year reported similar life satisfaction levels as those that did not win.

3.3 Latent class ordered probit

Using the conventional fixed effects models described in the previous sections, correct for intercept heterogeneity. One step further, is to model for slope heterogeneity; i.e. answering "who has the largest willingness to pay for reduced pollution". The model endogenously divides the observations-in a probabilistic sense -into separate classes, which differ by the parameters-slope and intercept of the relation between income and happiness. This model assumes that an agent *i* evaluates her well-being at time *t.* Let β_{it} denotes her answer, which belongs to the ordered set of labels $J = \{j_1, j_2 .. j_J\}$, where *J* denotes the label for *j=1,2…J*. The ordered probit (OP) model is usually justified on the basis of an underlying latent variable, LS, in our case, which is a linear function in unknown parameters of a vector of observed characteristics z (including all the independent variables in model 1), and its relationship to certain boundary parameters, μ. We can therefore write for simplicity the model:

$$LS^* = z'\gamma + u \tag{6}$$

So model (1) is related to the observed outcome LS as:

$$LS = \begin{Bmatrix} 0 \;\; if\, LS^* \leq 1 \\ j \;\; if \;\; \mu_{j-1} < LS^* \leq \mu_j,\; for 1 < j < J \\ J\; if \;\; \mu_{J-1} \leq LS^* \end{Bmatrix} \tag{7}$$

Under the assumption of normality the associated probabilities of (7) are (Maddala 1983):

$$\Pr(LS) = \begin{Bmatrix} \Pr(LS = 0 \mid z) = \Phi(\mu_{j=0} - z'\gamma) \\ \Pr(LS = j \mid z) = \Phi(\mu_j - z'\gamma) - \Phi(\mu_{j-1} - z'\gamma); for \; - < j < J \\ \Pr(LS = J \mid z) = 1 - \Phi(\mu_{J-1} - z'\gamma) \end{Bmatrix} \tag{8}$$

Formally, a latent variable c^* is defined, which determines latent class membership. This is assumed to be a function of a vector of observed characteristics x; with unknown weights β and a random disturbance term ε as:

$$c^* = x'\beta + \varepsilon \tag{9}$$

The overall probability of an outcome *j=1,2…J* is simply the sum of those respective classes and have the form:

$$\Pr(LS = j \mid x,z) = \Pr(c=1 \mid x)\Pr(LS = j \mid z, c=1) + ... + \Pr(c = J \mid x)\Pr(LS = j \mid z, c = J) \quad (10)$$

So, for example for those belonging to class 1we have:

$$P_{i|c} = \begin{cases} \Pr(LS = 0 \mid z, c=1) = \Phi(x'\beta)[\Phi(-z'\gamma_1)] \\ \Pr(LS = j \mid z, c=1) = \Phi(x'\beta)[\Phi(\mu_{1,j} - z'\gamma_1) - \Phi(\mu_{1,j-1} - z'\gamma_1)]; for\ - < j < J \\ \Pr(LS = J \mid z, c=11) = \Phi(x'\beta)[1 - \Phi(\mu_{1,J-1} - z'\gamma_1)] \end{cases} \quad (11)$$

The log likelihood function, for a random sample of *i=1,……,N* individual, can be written as:

$$l(\Theta) = \sum_{i=1}^{N}\sum_{j=0}^{J} h_{ij} \ln[\Pr(y_i = j \mid x_i, z_i)] = \sum_{i=1}^{N}\sum_{j=0}^{J} h_{ij} \ln[\sum_{c=0}^{C=1} P_{ij|c}] \quad (12)$$

The indicator function h_{ij} is

$$h_{ij} = \begin{cases} 1\ if\ \ individual\, i\ chooses\, outcome\ j \\ 0\ otherwise \end{cases} (i=1,.....,N; j=0,1,.....,J). \quad (13)$$

$P_{ij|c}$ are the choice probabilities of individual in being in choice outcome *j=0,…..,J* conditional on class membership *c*. The explanatory variables, such as income, are correlated with unobservable utility; therefore individual heterogeneity, in the sense that the utility function is not the same across individuals, is accounted for: both intercept and slope heterogeneity can play a role. Therefore, the individuals belong to a group defining a subpopulation, which is a generic term indicating a cluster within a heterogeneous population. Population heterogeneity can be observed or unobserved.

Heterogeneity is observed if it is possible to define the subpopulations based on an observed variable. For instance, gender or age might introduces heterogeneity in life satisfaction; therefore one can define two subpopulations for gender (i.e., males and females) or age groups based on the observed variables gender and age. In the context of observed heterogeneity, subpopulations are called groups, and group membership is known for each participant. The data can be analyzed using models for multiple groups. Multiple-group analyses are appropriate if the interest is to compare explicitly defined groups such as gender and age groups mentioned above. However unobserved heterogeneity differs from the multiple-group situation or interaction models, where the variables that cause the heterogeneity in the data are not known beforehand. Consequently, it is also not known to which of the subpopulations a respondent belongs, and it is not possible to divide the sample into groups. The subpopulation membership of the participants has to be inferred from the data. In the context of unobserved heterogeneity, the subpopulations are called latent classes because subpopulation membership is not observed but it is latent. However, this greater flexibility comes at the cost of assuming the exogeneity of pollution, which means that we are no longer relying on the panel fixed effect.

4. Data

We use the British Household Panel Survey (BHPS) an annual survey of a nationally representative sample of more than 5,000 households which started in 1991 and stopped in 2009. Individuals moving out or into the original household are also followed. Booster samples of around 400-500 households were added for Scotland and Wales at wave 9 (Taylor et al., 2010). The data period used in the current study covers the waves 1-18, i.e. years 1991-2009, including the booster samples.

The BHPS has been extensively used for empirical work on life satisfaction / happiness (see Clark and Oswald, 1994, for an early example). Based on the happiness literature the demographic and household variables of interest are household income[12], gender, age, family size or household size, labour force status, house tenure, marital status, education level, health status and local authority districts. Additionally, the regressions control for the day of the week, month of the year and the wave of the survey, and an area-specific trend to capture the effect of unobservable characteristics of the neighbourhood correlated both with pollution and satisfaction, which may vary over time.

The survey contains three questions regarding life satisfaction: one about overall life satisfaction and one about general happiness. Life satisfaction is reported on a 7-point scale from not at all satisfied to completely satisfied. General happiness is an ordinal variable measured on a 4-point scale and the specific phrasing of the question is the following "Have you recently been feeling reasonably happy, all things considered". The correlation between these two variables is 0.5089 and statistically significant. The last well-being measure examined in this study is GHQ "Caseness Scores" used by Clark and Oswald (1994). More specifically, the GHQ score combines the answer to twelve questions, each on a four-point scale. The GHQ level of mental distress score ranges from 0 to 12, where 12 is the lowest feeling of well-being, and 0 indicates the lowest mental distress. The correlation between "General Happiness" and GHQ is negative and significant (0.7343), while life satisfaction is also significantly negatively correlated to GHQ (-0.4906). The negative correlation is expected as higher values of "Life satisfaction" and "General happiness" are related to higher levels of self-reported well-being, while higher values of GHQ measure correspond to lower levels of well-being.

[12]The analysis was also conducted using individual level income; however this is affected by labour force participation which we do not explicitly model here.

We map air pollution data to the BHPS data. First, we use data on air pollution available from the Department for Environment, Food and Rural Affairs (DEFRA) website. This contains the exact location of air monitoring stations on a grid –easting and northing coordinates. Second, we have access to secure data on the BHPS' respondents' post codes, also expressed on grid references using easting and northing coordinates[13]. The unique feature of these restricted data is that information about the location of respondents' residence is available at a disaggregated level which allows us to identify far more accurately than has been possible with such a large-scale data set the local neighborhood each individual inhabits. The next step is to assign each individual to the closest air monitoring station using the Euclidean distance[14]. In robustness checks the inverse weighting distance method using 5 or 15 miles is applied (Currie and Neidell, 2005; Ferreira et al, 2013). The results are similar when we use the actual level of pollution at each monitor location with those calculated using the inverse weighting distance. Map 1 displays the locations of the air monitoring sites and reflects the distribution of the population in the country. There are 174 monitoring stations (not all monitors all pollutants) scattered along the main population centres, so that 69.15 percent of the population lives within 15 miles from a monitoring station. Individuals are allocated the average pollution level in the period preceding the interview. More specifically, different periods are considered; the day prior to the interview, weekly averages, monthly averages. The timing of the relationship between pollution and satisfaction is unclear; as such we report results for different periods, using either the pollution on the day prior to the interview or the average pollution level in the week or month preceding the interview.

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[13] Individuals' locations, produced by the Institute for Social and Economic Research (ISER) at the University of Essex, are known at 100x100 meter resolution.

[14] This is simply a matter of applying Pythagoras' theorem and using Euclidean distance. The required distance is the hypotenuse of a triangle. The other two sides of that triangle are, respectively, $(e_2 – e_1)$ and (n2 - n1), where e1 and e2 are the eastings of the two points, and n_1 and n_2 are their northings. The distance can be calculated by means of the following formula dist=$\sqrt{}(e_2-e_1)^2 + (n_2-n_1)^2$.

We focus on four of the main air pollutants: ground-level ozone (O_3), sulphur dioxide (SO_2), carbon monoxide (CO) and nitrogen dioxides (NO_X)[15]. The air pollutants are based on daily frequency and measured in $\mu g/m^3$. There are 110 monitoring stations for SO_2, 124 for O_3, 105 for CO and 173 for NO_X[16]. Map 2, 3, 4, 5 depict the annual concentrations for SO_2, O_3, NO_x and CO respectively for the years 1999 and 2005. For all these pollutants, there is a large heterogeneity in level in the country. It is also clear that air quality has improved substantially over the period in general but this was not homogenous, and some areas have even experienced deterioration; for example the Scottish Highlands and the South West of England have seen their SO_2 concentration rise from below 10 $\mu g/m^3$to between 10-20 $\mu g/m^3$. Since the identification relies on non-movers, the pollution effect is identified from temporal variation in pollution in models including individual fixed effects.

In table 2 the summary statistics of air pollutants, income and meteorological data are reported for the full and non-movers samples. The income of the non-movers sample-both individual and household- is significant higher than the incomes of the movers sample but the differences in air pollution emissions between the two samples are not; as such it is unclear whether moving is related to pollution or that non-movers are financially constrained. Furthermore, t-statistics for the two well-being measures-Life satisfaction and Happiness- are reported in table 2, indicating that there are differences between the two sample, with the non-movers sample reporting higher levels of well-being than the movers in years before they move.

Table 3 presents the correlation matrix between the various pollutants and the life satisfaction measures. These correlations are based on the average pollution levels at the

[15]Particulate matter is not examined as the data cover only few urban areas (17 air monitoring stations), like Manchester, Birmingham, London, Glasgow, Belfast etc., and are only available from wave 12 onwards.
[16]The data can be found at the Department for Environment Food and Rural Affairs (DEFRA, http://uk-air.defra.gov.uk).

nearest monitoring station at the day before the interview. The correlation between sulphur dioxide, nitrogen oxides and carbon monoxide is positive, while ground-level ozone is negative correlated with the other air pollutants examined. The negative correlation between O_3 and the other pollutants might be induced by seasonal variations in the occurrence of these pollutants, as discussed next. The correlation between life satisfaction and happiness is positive and significant and equal at 0.6. On the other hand the correlation between life satisfaction, happiness and GHQ caseness score are negative and equal to 0.52 and 0.78 respectively.The correlation between happiness and GHQ measure is higher than between life satisfaction and the other two well-being measures. Regarding the correlation between the well-being measures and the air pollutants examined is negative and significant. More over, the negative association is stronger concerning the life satisfaction followed by GHQ caseness score and happiness.

In table 4 we regress pollution records by month and year after accounting for monitoring station fixed effect to assess the monthly and yearly variation in pollution. It should be noted that the estimates are based on single regressions for each pollutant. Based on table 4 a clear seasonal variation can be observed for each of the pollutants. The air pollution concentration for sulphur dioxide, carbon monoxide and nitrogen oxides is higher during the winter, while for ozone the lowest concentrations are reported during the period October to December, this is conform to expectations based on the physical properties of these pollutants (see Annex). From the year effect estimates, it is clear that overall pollution has been reduced over time. These confirm that it is important to control for month and year of survey in the analysis, which we do using local linear trends.

In table 5 the probit regressions for moving status are reported. More specifically, the dependent variable takes value 1 if the respondent has moved within Great Britain and 0 otherwise. None of the pollutants are significant at explaining mobility, however, income has a negative effect on the probability of moving.

One issue is whether the pollution is as good as randomly assigned to non-movers. Based on summary statistics reported in table 2 the difference of air pollution levels between movers and non-movers sample is insignificant, while the income is significantly higher for non-movers confirmed by the "movers-stayer" model by Blumen et al. (1955). In this model some workers are expected to be more likely to move than others. This instability is assumed to lower productivity, and thereby to reduce the wage of movers below the wage of non-movers. In addition approximately 10% of individuals actually move house every year. This proportion has remained relatively constant across the period of the BHPS survey. Moreover, almost two-thirds of the movers remain in the same Local Authority district. Furthermore, based on table 5 air pollution is not significant factor on moving status, with the exception of NO_X, while employment status and income are significant factors of moving status. Almost 20% of the unemployed move, compared with 9% of employees and 8% of the self-employed.

5. Empirical results and discussions

Equation (1) is estimated separately for each pollutant. Column (1) in table 6reports the OLS and Fixed Effects model estimates of life satisfaction with regards to air pollutants based on weekly averages of the pollutant; on the day prior the interview and over the six previous days. Age, education level, job status, marital status and gender have the expected signs on life satisfaction, consistent with other studies' findings (Clark and Oswald, 1996). Temperature presents an inverted U-shaped curve with a maximum point around 33-35 of Celsius degrees similar to Levinson (2012). Wind speed and precipitation present the expected negative signs on life satisfaction.

In column (3), (5) and (7) we report the same estimates for ground-level ozone, nitrogen oxides and carbon monoxide respectively. In all cases, the air pollutant coefficient is negative and statistically significant. More specifically, we interpret the coefficients by saying that an increase of a standard deviation in SO_2, results on average, in an increase of $\beta_1 * s_y$ in the dependent variable. The parameter β_1 denotes the standardised coefficient of the air pollutant, while s_y denotes the standard deviation of the dependent variable. Hence, based on table 7 and OLS estimates, increasing SO_2 by one standard deviation reduces well-being by 0.0031, while based on the FE estimates increasing SO_2 by one standard deviation reduces well-being by 0.0042 units. Regarding O_3 the effects are stronger as the well-being is reduced by 0.0032 and 0.0068 for one standard deviation increase based on OLS and FE estimates respectively. The reductions for NO_X are 0.0026 and 0.0018 units on well-being based respectively on OLS and FE results. Finally, increasing CO by one standard deviation reduces well-being by 0.0031 units. All the air pollutant coefficients are statistically significant.

We now compute the marginal willingness-to-pay (MWTP). This is the level of household income that makes individuals indifferent to a drop of a standard deviation in a pollutant. Based on OLS estimates using the non-movers sample and household income the average marginal willingness-to-pay (MWTP) for a reduction in SO_2 is £507 and £636 per year based on OLS and FE estimates. Luechinger (2009) using the German Socio-Economic Panel (GSOEP), found that for a one-unit μg/m^3 decrease in SO_2, the WTP ranges between $300-500, while the MWTP value derived from the FE model in this study is \$1,000. The estimates differ for various reasons. Firstly, the country of interest is different. Secondly, our estimates are based on standard deviation, rather than on mean values. Thirdly, the air mapping is based on post codes, which provides more precise results. The respective MWTP values for O_3 are £680 and £780. The MWTP values are lower for NO_X and CO and are equal at £428 and £437 based on OLS estimates, while the respective values derived from FE regressions are £437 and £456. These results are not comparable with other studies, because the above-mentioned air pollutants have not been examined.

We now test the sensitivity of these results to different sample and different measures of income using the fixed effects model. Specifically, Table 7 reports estimates for the full sample, non-movers and movers and for different measures of income, personal or household. The results are quantitatively similar to those presented above. Sample definition does not affect our estimates but using household rather than individual income leads to higher estimates of the willingness to pay.

In Table 8, we report estimates of MWTP for alternative samples and sub-groups of the population. First, we assess the sensitivity to the timing of the pollution variable, using either monthly average or previous day, rather than weekly average. Estimates based on monthly averages are significant and result to larger MWTP than previously estimated for all pollutants. However, daily pollution level is not significantly correlated with happiness; the coefficient is in general smaller. This might be related with the fact that individuals need to be exposed for some time before their satisfaction is affected and the daily measure is only a noisy measure of "recent" exposure. The findings are not consistent with the study by Levinson (2012) who claims that people become habituated to their environments and respond only to daily deviations from the local norm. This can be explained by the following: Firstly, the daily measure can be a noisy measure because of the missing values which results to significant sample reduction. This is a major issue because in the case examined we have a panel data; therefore there might be missing values for the same individuals across time. Even if the second monitoring station or inverse weighted distance is assigned, leaves the data with a measurement error. This is due the fact that in almost all cases, with the exception of London area, the second monitoring station is significantly longer from the respondent's post code than the closest monitor is. May this not be the case in the study by Levinson (2012) or at least it is not mentioned. Secondly, the perceived risk (PR) is an important factor. More specifically PR is defined as an individual's assessment of air pollution that might pose medium or long-term threats to their health and well-being (Adeola, 2007; Li et al., 2014). PR is assumed to have a negative impact on a respondent's happiness and this hypothesis is supported by Van Praag and Baarsma (2005), who found that perceived noise negatively influences people's happiness. Also it is supported by Rehdanz and Maddison (2008) who studied the impact of perceived air pollution on happiness in Germany and found that higher perceived air pollution significantly diminishes happiness. Moreover, the regressions control for monthly fixed effects, which capture for the monthly seasonality in air pollution. Concluding, the effects of air pollution on happiness through PR are stronger in the medium term rather the daily frequency, as there might be persistence on the air pollution which can be captured by weekly and monthly averages. In addition, SO_2 and O_3 are detectable air pollutants as they are responsible for the formation of winter and summer smog respectively. Finally, Levinson (2012) maps the air pollution on the respondent's county location, which is a rather large area, while this study relies on post codes.

As stated above, our favoured model is for a sample residing less than 10 miles away from a monitoring station. There is a trade off with the distance to the monitoring station. A smaller distance reduces measurement error but reduces sample size. In panel

B, we report estimates for samples locating at a distance of less than 5 or 15 miles from the monitoring station respectively.

Distance appears to be broadly negatively correlated with willingness to pay; estimates of the MWTP tend to be larger for the sample living closer to a monitoring station, indicating that estimates based on less precise measure of pollution suffer from substantial attenuation bias. As such, studies relying on national average level of pollution are likely to severely underestimate willingness to pay.

We now assess the heterogeneity of our results to the individual characteristics. In panels C1-C2, we test the heterogeneity of our results with regards to urbanicity as individuals may have selected themselves according to their dislike for pollution. Alternatively, since urban environments tend to be more polluted, city dwellers may have a greater willingness to pay if the MWTP is heterogenous in pollution level. The MWTP is two to five times greater in urban areas than in rural. More specifically, for SO_2 the MWTP is £1,162 and £268 for urban and rural areas respectively. Similarly for O_3 the MWTP is £1,226 and £362. Regarding NO_X and CO the MWTP values for urban areas are £1,226 and £559 respectively, while for rural areas are insignificant. Respondents located in urban areas are more sensitive to air pollution, maybe because of its higher level in cities (Ferreira et al., 2013); therefore they might be willing to pay more. A possible explanation for this difference is given in Fransson and Garling (1999) that urban residents are more exposed to the signs of environmental deterioration such as air pollution. This hypothesis receives support in several studies (Arcury and Christianson 1990; Howell and Laska 1992). Moreover, city dwellers are richer on average.

In panel D, we investigate possible non-linearity in the effect of pollutant by specifying it as a quadratic term. The coefficients of the air pollution in quadratic terms are found to be insignificant similar to other studies (MacKerron and Mourato, 2009; Luechinger, 2009). Similarly, quadratic terms in income are never found to be significant as in the studies by MacKerron and Mourato (2009) and Luechinger (2009).

In panels E-F the estimates regarding the gender and age groups are reported. It can be shown that women are willing to pay more than men and the excess is ranging between £15-£145. Regarding the age the younger and older age groups are willing to pay more for the reduction in air pollution as it has been found in other studies (Schahn and Holzer, 1990; Mohai, 1992; Fransson and Garling, 1999; Hunter et al., 2004; Menz and Welsch, 2012; Silva et al., 2012). More precisely, the age groups 16-34 are willing to pay substantially more for the reduction in air pollution. For example, with regards to SO_2, the estimated MWTP for the 35-44 age group is £280 but reaches £1,723 for the 25-34, and £434 for individuals older than 64. We cannot distinguish whether this is a cohort effect or an age effect. However, these results can mean two things. Firstly, the young age group might be consisted by more educated people who are more environmentally aware about the negative effect of air pollution on health. Secondly, health is negatively associated with age; thus older people are willing to pay more in order to be happier.

Individuals with a poorer health status might be willing to pay more for air quality improvement as they are more likely to be negatively affected by pollution. We thus split the population by health status. For O_3 and NO_X, we indeed find that individuals who reported poor health status are willing to pay more than those whose health status is considered as excellent-good. More specifically, individuals with poor health status are likely to pay £389 and £159 more for reduction in O_3 and NO_X respectively. However, we find exactly the opposite for SO_2, where individuals with excellent-good self-reported health status are willing to pay more than twice as much as those in poor health status for a reduction in pollution. Note, that the coefficient for CO is insignificant in both samples. Overall, the evidence that the willingness to pay for reduced pollution depends on health status are rather mixed.As an alternative for health measure we also examine the willingness to pay separately for smokers and non-smokers. For all pollutants, smokers have a lower willingness to pay for a reduction in pollution, which is consistent with the assumption that smokers value their health less. Overall, the evidence mostly supports the assumption that health status affects willingness to pay. These differences may be underestimated due to reverse causality whereby people who value their health more, invest more in preserving it, including willingness to reduce pollution and are in better health.

We now investigate the model specification further. We first split the panel into two periods since pollution levels differ substantially over time. During the period 1991-1999 air pollution was more prevalent and the estimated willingness to pay larger, especially so for O3. This can be explained by the fact that in 1999, the Pollution Prevention and Control Act 1999 (http://www.legislation.gov.uk/ukpga/1999/24/contents), has been implemented. Under this new regime, Local Authorities are required to regulate the smaller industries, whereas the Environment National Agency regulates the larger industries. The purpose of this Act is to prevent and to control pollution. In panel J the estimates for individuals living in low and high pollution areas are reported. Individuals located in high pollution areas are willing to pay more by roughly £100, £300 and £50 for a reduction in SO_2, O_3 and NO_X respectively than the respondents located in low pollution areas. The results for CO are insignificant.

We also assess the sensitivity of our estimates to alternative measures of well-being. We thus estimate the model with two alternative measures “Life Satisfaction” and “CHQ”. This is only possible for a subset of the sample for which the life satisfaction question was asked. Reassuringly, the MWTPs are very similar to those found when estimating it with happiness and, in both cases, are never differ by more than 5%.

We now estimate a dynamic panel so as to solve the problems of reverse causality, while accounting for the correlation of the time-invariant characteristics with the explanatory variables and the autocorrelation by specifying the model in first differences and using lagged levels of the endogenous variables as instruments. More specifically, the first-differenced lagged dependent variable-the self-reported well-being- is instrumented with its past levels accounting for the autocorrelation problem (see eq. 5). In all cases the coefficient of happiness with one lag has the expected positive sign; happiness status has some persistency pattern, and it is significant for both personal and household income.

As in the static model, the coefficients on air pollutants are negative and significant and we can compute the MWTP (Table 9). The MWTP values for SO_2 are £1,152 and £927 for the full and non-movers sample; higher than those estimated from the static fixed effects model. The respective values for O_3 are £1,037 and £945, for NO_X are £344 and £365 and for CO are £450 and £486.

We can say that all our results are robust for the following reasons: First, the instruments used in our regressions are valid; the Hansen test does not reject the hypothesis of exogeneity and validity of lagged variables in levels and in difference as instruments. Secondly, we note that there is no second-order autocorrelation of errors for difference equation, because the test of second order autocorrelation (AR2) does not allow rejecting the hypothesis of absence of second-order autocorrelation. The dynamic GMM model introduces a lagged dependent variable on the right-hand-side of the equation, which substantially changes the interpretation of the coefficients for the independent variables. Such an analysis also introduces more methodological considerations, including the ability to choose whether the independent variables are endogenous and exogenous. Such a choice can substantially change the significance of any association between well-being and some important independent variables. A further advantage of dynamic panel methods over standard fixed effects analysis is the ability to distinguish between long-run effects and contemporaneous effect of various variables on happiness. The results directly obtained from such an analysis are the new information or contemporaneous effects, and a quick post estimation calculation can provide the long-run coefficients. The lagged dependent variable tells us the influence of the past. The lagged happiness coefficient is positive, suggesting a persistence or inertia effect from previous happiness; lagged happiness being positively associated with current happiness. That the coefficient is small means that the influence of the past is minor, demonstrating that what are most important for the determination of current happiness are current circumstances and events. To a greater or lesser degree, every study mentioned previously that uses GMM for dynamic estimation of happiness finds a small, positive coefficient (Powdthavee, 2009; Wunder, 2012) as we find in this study.

We now account for possible heterogeneity in the effect and estimate the model with latent class ordered probit. Latent class models allow the parameters of the unobserved (latent) individual utility function to differ across individuals i.e. slope heterogeneity (Tinbergen, 1991; Clark et al., 2005). However, latent class ordered probit models allow only for random effects. On the other hand, the generalized latent class ordered probit model relaxes the parallel assumption and it allows each region to influence differently each response category. Thus, the model permits the reference scale to be different for each threshold. In addition, the model relaxes the parallel assumption on income as previous research shown, income may exhibit slope heterogeneity (Clark et al., 2005). Income may affect the reference scale of each respondent, with people being more likely to report a low or high happiness level, for any given level of true individual well-being, according to their income.

In column (1) of table 10 the ordered probit regressions are reported, while in columns (2)-(4) the latent class ordered probit regressions for the air pollutants, regarding the non-movers sample respectively are summarised. Latent class techniques model simultaneously intercept and slope heterogeneity in the relationship between income, air pollution and reported well-being. The statistical model endogenously divides the observations -in a probabilistic sense- into separate classes or groups, which differ by the parameters -slope and intercept- of the relation between income, air pollution and self-reported well-being. Therefore, this approach allows for heterogeneity in the intercept of the regression line, but also in the slope. In table 10 the estimates for the four air pollutants examined are reported. Based on the results, the as income increases, the probability of reporting low level of happiness decreases. These findings are consistent with the study by Boes and Winkelmann (2006), which suggest that income buys happiness up to a certain level, after which further increases in income have lower or insignificant effects on happiness.

For SO_2 the willingness to pay is significant only for classes 1 and 2, the least satisfied. Additionally, the willingness to pay is more than twice as large in class 1 (much less happy) as the average effect and three times as large as the one estimated for class 2. The membership of class 1 is only 2.96 per cent. For classes 2 and 3 its 10.33 and 71.41 per cent respectively. Thus, less than 14% of individuals are willing to pay to reduce SO_2 pollution.

For the other air pollutants, the coefficients of the air pollutant are significant in all classes and in general are largest in class 1. For CO the willingness to pay to reduce air pollutant is very similar in all classes. Overall based on the MWTP values the individuals are willing to pay more for SO_2 and O_3. Regarding SO_2, O_3 and CO the least satisfied respondents (classes 1 and 2) are willing to pay more. More specifically, the marginal willingness to pay for classes 1 and 2 and SO_2 is £1,399 and £403, while the MWTP for class 3 is £260. Regarding O_3 and NO_X the MWTP is higher for class 2 at £895 and £582 respectively, followed by classes 1 and 3 with respective MWTP equal at £442 and £616 for O_3 and £236 and £332 for NO_X. The MWTP for CO is very similar among classes ranging between £480-£540. The latent class model highlights significant level of heterogeneity in the willingness to pay within the population, especially for SO_2 and O_3.

Overall, the results provide evidence that air pollution and income parameters are heterogeneous with respect to happiness distribution; in other words, there is *slope heterogeneity* in the happiness estimates. Increases on income are associated with lower probabilities of reporting low levels of happiness. On the other hand, improvements in environmental quality decrease the probability of reporting a low level of happiness, which is in contrast with the effects of income, where income is positively associated with the probability of reporting a low happiness level. Thus, the results indicate that in order to achieve high levels of happiness and well-being, other factors than income may play a major role.

6. Conclusions

This study has used a set of panel micro-data on self-reported well-being happiness from the British Household Survey. The results showed that the monthly MWTP for sulphur dioxide ranges between £636-£660 per year, while the MWTP values for ground-level ozone, carbon monoxide and nitrogen oxides range from £780-£864, £456-£492 and £372-£360 per year respectively. The estimated MWTP are higher using dynamic panel data and Arellano-Bond estimator, and they range from £927 to £1,150 across pollutants. The estimates are robust to a battery of model specifications and robustness checks. Regarding, the latent class ordered probit model the results show that the least satisfied classes are willing to pay more for a reduction in air pollution but that the majority of the population is not willing to pay.

The importance of this study comes from the fact that the analysis relies on detailed micro-level data, using highly spatially disaggregated data based on grid references, capturing far more precise the air pollution effects, which are not captured in previous studies. In addition, more advanced econometric techniques have been employed (dynamic panel, latent class model estimation, which allow for heterogeneity in the effect). This study reveals important points. Firstly, the results showed that air pollution has direct effects on individuals' well-being. Secondly, there is evidence of a substantial trade-off between income and air quality, which is the compensating differential for air pollution. This study is rather a large scale research. However larger-scale researches, using more than one country and based on high spatially disaggregated data is suggested in order to clarify the potentially complex links between well-being and individuals' exposure to air pollution. This could offer further insights for achieving simultaneously happier, cleaner and more sustainable cities.

Despite the drawbacks of the LSE and the limitations surrounding the monetary values for WTP, as it has been discussed in the previous parts, still useful information can be derived from this approach. For example individuals residing in urban and high polluted areas, younger and older individuals are more adversely affected by air pollution. In addition LSE estimates point towards a substantial residual shadow value associated with air pollution that is not captured in hedonic and housing pricing models. Consistent with earlier life satisfaction valuation literature, discussed in the previous parts, this finding challenges the validity of the assumption of equilibrium in housing markets. In this context, the life satisfaction approach may serve as a useful complement to the hedonic method in the valuation of non-market goods.

There are various areas for further future research. Firstly, important insights will be gained by additional comparisons between the life satisfaction approach and traditional methods, such as stated and preference methods, choice modelling and others. Another area for future research refers on improvements of the LSA. One major issue is the need for more precise estimates of the income effect on well-being measures, as it has been mentioned in the introduction part. So far, the studies based on exogenous changes in income are rare, and these are subject of criticism, as it has been discussed in the introduction part. The third area refers on the subjective well-being measures. More specifically, there is still the concern that using these measures, the estimates are systematically biased due to conceptual problems and contextual factors, such as question order effects and the lack of intergroup.

Generally, the results show that the life satisfaction approach contains very useful information on individuals' preferences and at the same time expands the economic tools in the area of non-market evaluation. More specifically, arguments about reducing air pollution is already know to policy-makers, including the requirements of EU and domestic law, the prospect of improved public health and reduced health spending, and the potential co-benefits in relation to anthropogenic climate change. This study sought to assess how the use of environmental quality at high spatial resolution could advance the empirical literature examining connections between air quality, weather and other socioeconomic factors and life satisfaction. Using the detailed geographical level in this study it becomes possible to examine and strengthen existing arguments in favour of policies to reduce air pollution, framed both in terms of conventional economic efficiency analyses, and in wider political and ethical and legal terms.

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Appendix A

Sulphur dioxide (SO_2) is a colourless gas, released from burning fossil fuels like coal and oil. It is one of the main chemicals that cause acid rain. Industrial activities that burn fossil fuels containing sulphur, especially power stations and oil refineries can be important sources of sulphur dioxide. SO_2 has long been recognised for its role in forming winter-time smogs. High concentrations of SO_2 can result in breathing problems for asthmatic children and adults. Furthermore, short-term exposure has been linked to wheezing, chest tightness and shortness of breath, while long-term exposure is associated with respiratory illness and cardiovascular diseases (Harrison, 2001)[17].

Ozone (O_3) is a colourless, odourless gas at ambient concentrations and is the primary constituent and component of smog. Motor vehicle exhaust and industrial emissions, gasoline vapours, and chemical solvents as well as natural sources emit NO_X and Volatile Organic Compounds (VOC) that help form ozone. O_3 is known as a summer-time air pollutant, because of the highest values occurring during the high average temperatures[18]. The effects of ground-level ozone on health include chest pain, coughing, throat irritation, and congestion, while it can worsen bronchitis, emphysema, and asthma, as it can reduce lung function and inflame the linings of the lungs (Harrison, 2001).

Nitrogen oxides (NO_x) are formed in the atmosphere mainly from the breakdown of nitrogen gas (NO_2). NO_2 is the component of greatest interest and the indicator for the larger group of nitrogen oxides and forms quickly from emissions from cars, trucks and buses, power plants, and off-road equipment. The effects on health are the same as ozone's (Harrison, 2001). The threshold for human protection health is 200 $\mu g/m^3$.

[17]The daily limit value for the protection of human health is 125 $\mu g/m^3$. More specifically, sulphur dioxide emission should not be exceeded 125 $\mu g/m^3$ more than 3 times a calendar year.
[18]The UK objective for protection of human health is 100 $\mu g/m^3$for O_3 with no more than 10 exceedences per year.

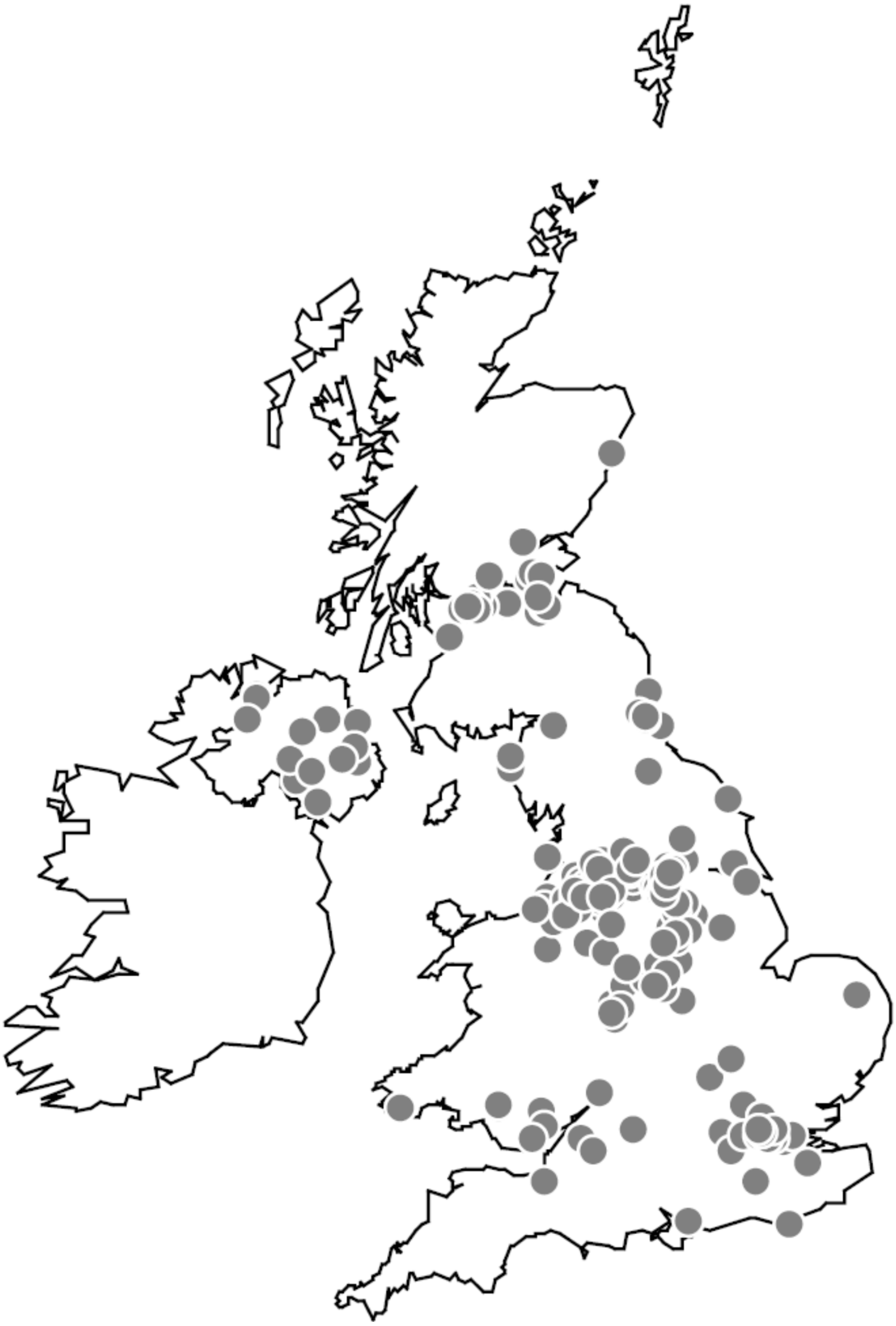
Carbon monoxide (CO) is an odorless, tasteless, colorless and toxic gas. Carbon monoxide is produced as a by-product of combustion. Any combustion process, fuel burning appliance, vehicle or other device has the potential to produce carbon monoxide gas. The largest source is road transport, with residential and industrial combustion making significant contributions. It substantially reduces capacity of the blood to carry oxygen to the body's tissues and blocks important biochemical reactions in cells. People with existing diseases, which affect delivery of oxygen to the heart or brain, such as angina, are at particular risk (Harrison, 2001)[19]. Arceo-Gomez et al. (2012) using data for Mexico found that an increase of 1 parts per billion in carbon monoxide and particulate matter over the last week results respectively in 0.0032 and 0.24 infant deaths per 100,000 births.

[19]The UK objective for protection of human health for CO is 10 $\mu g/m^3$as running 8 hour mean

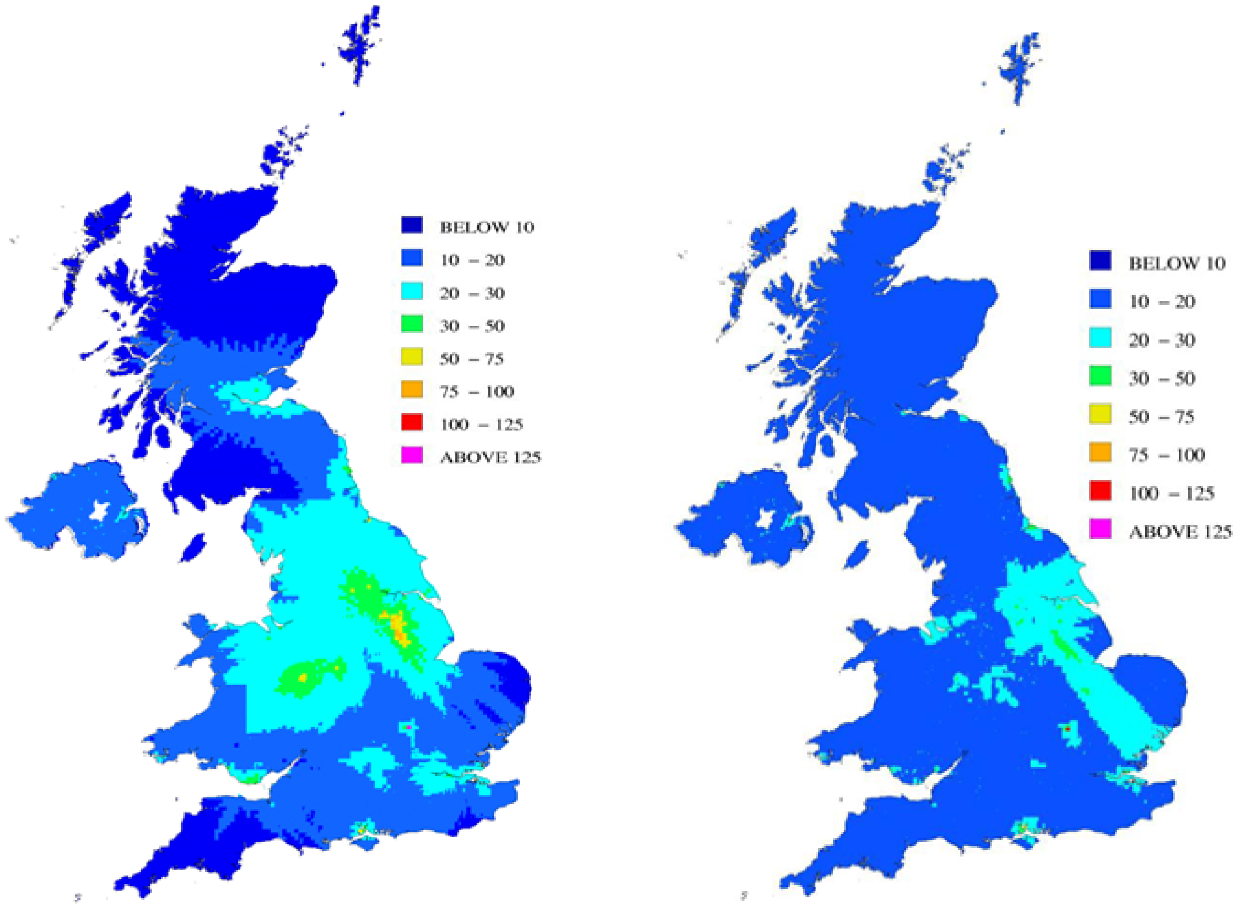
Table 1. Studies for Willingness to Pay Relatively to Air Pollution

Study	*Method*	*Air pollutant-subject*	*Period*	*Results Reference year 2012*
Smith and Huang, 1995	Hedonic value models	Total suspended particulates (TSP)	1967-1988	\$0-\$413
Bayer et al., 2009	Hedonic value models	Total suspended particulates (TSP)	1990 and 2000	\$198
Moaz, 2005	Hedonic value models	Total suspended particulates (TSP)	2000	\$79
Wang and Whittington, 2000	Contingent valuation	air pollution clean-up plan	1995	\$533
Loehman and De, 1982	Contingent valuation	air quality improvement program illness	1977	\$26-\$172
Loehmanet al.1985	Contingent valuation	air quality improvement program	1980	\$1,042 Los Angeles and \$267 in San Francisco
Hall et al.1992	Contingent valuation	Particulate matter (PM_{10})	1990	\$36
Loehmanet al.1994	Contingent valuation	air quality improvement program health	1980	\$35
Hammitt and Zhou (2006)	Contingent valuation	Sulphur dioxide (SO_2) Particulate matter (PM_{10}) for cold, chronic bronchitis and mortality	1999	\$4-\$7.9 for cold, \$658-\$1,317 for chronic bronchitis and \$5,530-\$22,252 for mortality
Welsh, 2002	Life satisfaction	Nitrogen dioxide (NO_2)	1990 and 1995	\$218
Welsh, 2006	Life satisfaction	Nitrogen dioxide (NO_2) and Lead (Pb)	1990-1997	\$737 for NO_2 and \$261 for Lead
Ferreira et al. (2006)	Life satisfaction	Particulate matter (PM_{10})	2001	\$1,779
Di Tella and MacCulloch (2007)	Life satisfaction	Sulphur dioxide (SO_2)	Mid of 1990s	\$255
Luechinger (2009)	Life satisfaction	Sulphur dioxide (SO_2)	1994	\$305 \$518 (IV)
MacKerron and Mourato (2009)	Life satisfaction	Nitrogen dioxide (NO_2)	2007	\$2,340
Ferreira and Moro (2010)	Life satisfaction	Particulate matter (PM_{10})	2001	\$1,528
Luechinger (2010)	Life satisfaction	Sulphur dioxide (SO_2)	1979-1994	\$240 \$494 (IV)
Levinson (2012)	Life satisfaction	Particulate matter (PM_{10})	1973-1996	\$896
The current study	Life satisfaction	SO_2 O_3 NO_X CO	1991-2009	\$1,004 (SO_2) \$1,232 (O_3) \$588 (NO_X) \$720 (CO)

Map 1. Distribution of Air monitoring Stations in the UK 2005



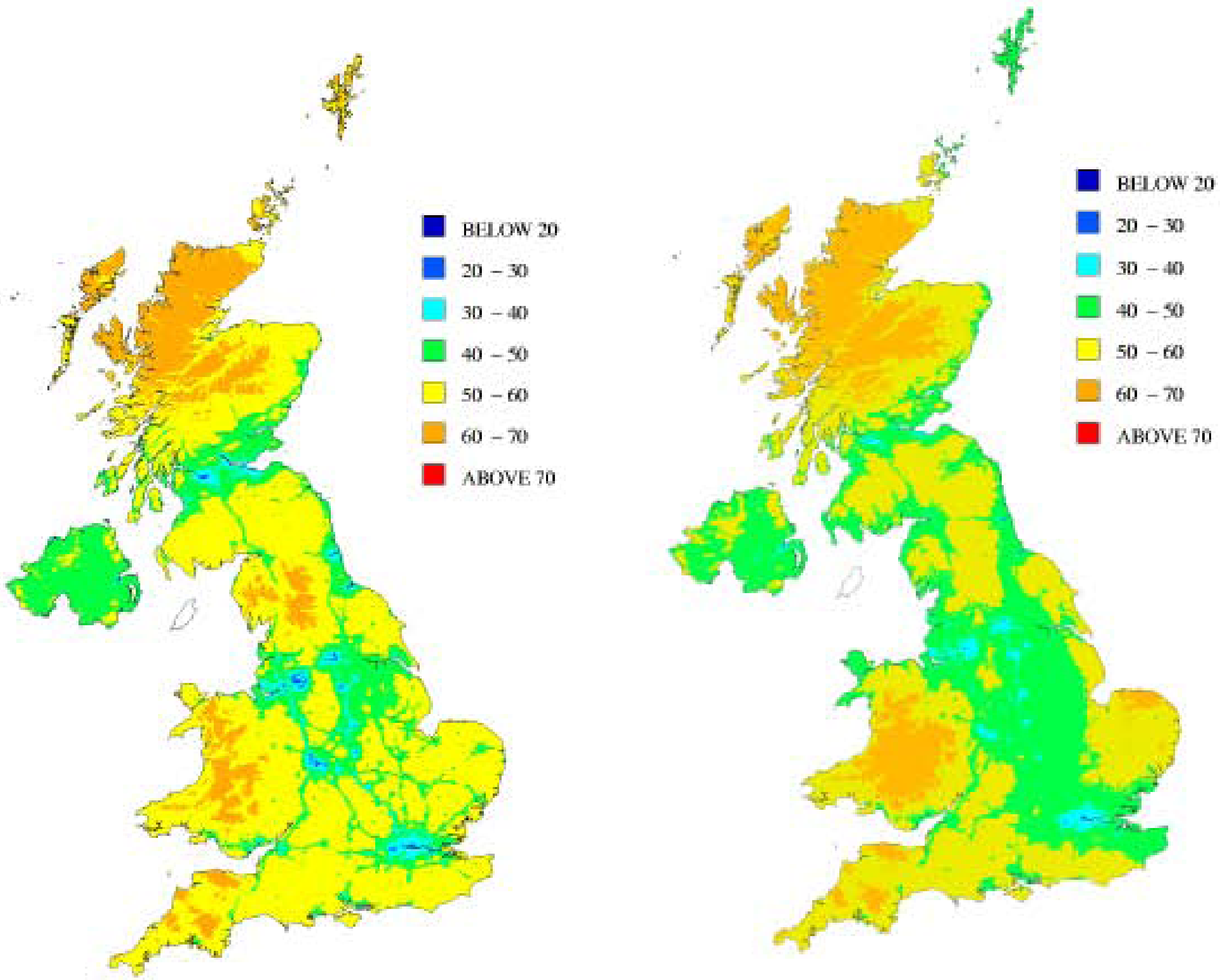
Map 2. SO_2 Concentrations Expressed in μg/m^3



1999 **2005**

Sources:
1. UK air quality modelling for annual reporting2000on ambient air quality assessment
2. Air Pollution in the UK 2006, A report prepared by AEA for Defra and the Devolved Administrations

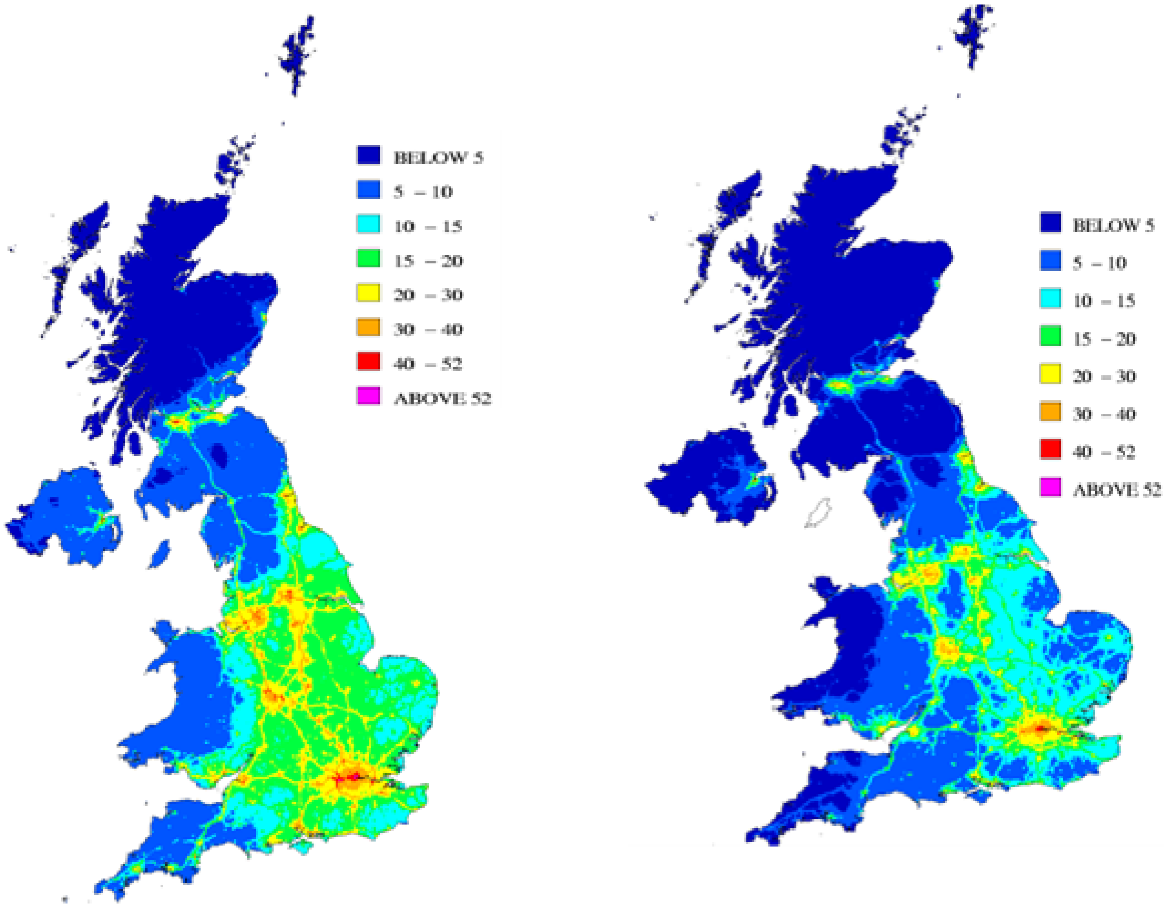
Map 3. O_3 Concentrations Expressed in µg/m^3



1999 **2005**

Source: Consultation on Ozone in the United Kingdom, (2008). DEFRA
http://archive.defra.gov.uk/environment/quality/air/airquality/publications/ozone/documents/aqeg-ozone-report.pdf

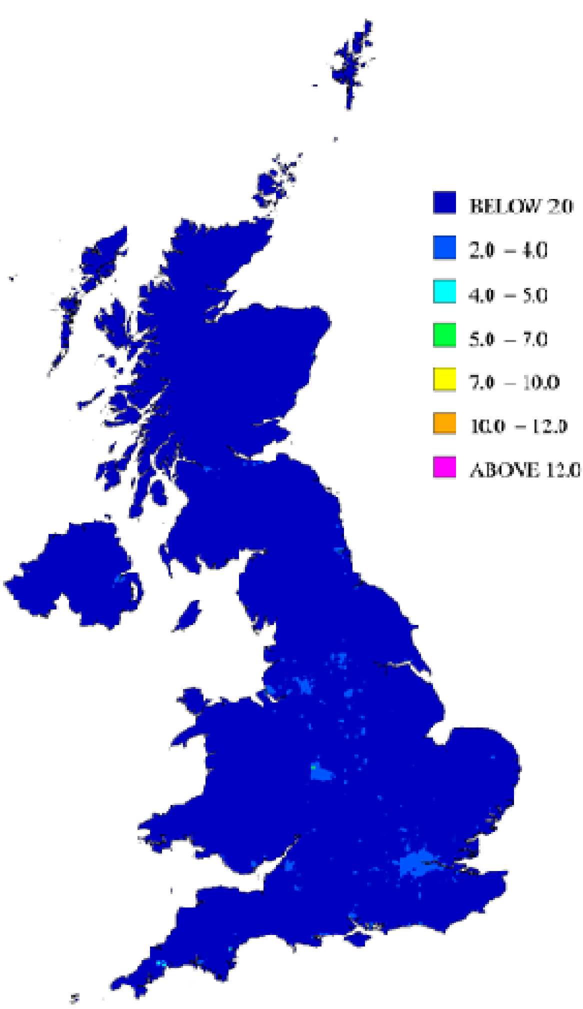
Map 4. NO_X Concentrations Expressed in µg/m^3



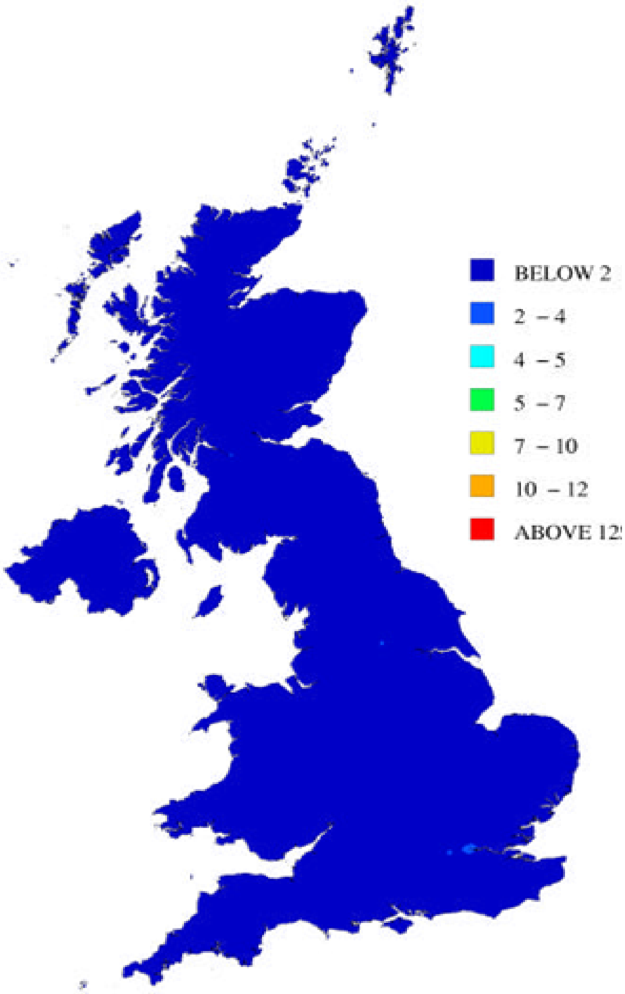
1999 **2005**

Sources:
1. UK air quality modelling for annual reporting2000 on ambient air quality assessment
2. Air Pollution in the UK 2006, A report prepared by AEA for Defra and the Devolved Administrations

Map 5. CO Concentrations Expressed in μg/m^3



1999



2005

Sources:

1. Projecting and mapping carbon monoxide concentrations in support of the Air Quality Strategy review, A report produced for the Department for Environment, Food and Rural Affairs, the Scottish Executive, the National Assembly for Wales and the Department of the Environment in Northern Ireland
2. Air Pollution in the UK 2006, A report prepared by AEA for Defra and the Devolved Administrations

Table 2. Summary Statistics of Income and Air Pollutants

Variables	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
		Panel A: Total Sample		
Personal income	1,115.378	1,167.831	0.0	72,176.51
Household income	2,449.341	1,970.468	0.0	86,703.29
Sulphur Dioxide (SO_2)	7.758	8.739	0.0	291
Ozone (O_3)	34.655	18.204	0.0	137
Nitrogen Dioxides (NO_X)	93.474	120.078	0.1	1,742
Carbon Monoxide (CO)	0.745	0.695	0.0	10.7
Average temperature	50.660	5.907	22.5	77.55
Wind speed	8.197	4.037	0.0	35.2
Precipitation	3.344	4.476	0.0	49.9
		Panel B: Non-Movers		
Personal income	1,142.206	1,181.836	0.0	71,058.95
Household income	2,516.326	1,981.367	0.0	72,927.47
Sulphur Dioxide (SO_2)	8.823	16.075	0.0	291
Ozone (O_3)	34.645	18.346	1.0	124
Nitrogen Dioxides	90.839	118.914	0.0	1,742
(NO_X)	0.768	0.744	0.0	10.7
Carbon Monoxide (CO)	50.846	5.937	22.5	77.55
Average temperature	8.103	3.903	0.0	33.2
Wind speed				
Precipitation	3.316	4.460	0.0	49.9
		Panel C: Air pollution statistics for the interview day		
Variables		*Standard Deviation*	*Minimum*	*Maximum*
Sulphur Dioxide (SO_2)		7.725	0.0	160
Ozone (O_3)		16.938	0.0	133
Nitrogen Dioxides		106.055	1.6	1,138
(NO_X)		0.508	0.0	6.7
Carbon Monoxide (CO)				
		Panel D : t-statistics for differences between non-movers and movers sample		
Variable	*t-statistic*	*Variable*	*t-statistic*	
Personal income	5.0135***	Carbon Monoxide (CO)	0.7364	
Household income	8.6022***	Average temperature	-2.9705***	
Sulphur Dioxide (SO_2)	-0.0005	Wind speed	-1.0699	
Ozone (O_3)	1.2912	Precipitation	9.5491***	
Nitrogen Dioxides (NO_X)	0.9355	Life Satisfaction	6.1642***	
Happiness	13.2429***			

The air pollutants are measured in micrograms per cubic meter (µg/m3), *** indicates significance at 1% level

Table 3. Correlation between Air Pollutants and Life Satisfaction Measures

	Sulphur Dioxide	Ground-Level Ozone	Nitrogen Oxides	Carbon Monoxide	Happiness	Life Satisfaction
Ground-Level Ozone	-0.2107*** (0.000)					
Nitrogen Oxides	0.5279*** (0.000)	-0.5204*** (0.000)				
Carbon Monoxide	0.4089*** (0.000)	-0.0042*** (0.000)	0.2676*** (0.000)			
Happiness	-0.0131*** (0.0004)	-0.0269*** (0.000)	-0.0091*** (0.0006)	-0.0085** (0.0127)		
Life Satisfaction	-0.0189*** (0.000)	-0.0297*** (0.000)	-0.0102** (0.0125)	-0.0096** (0.0432)	0.5883*** (0.000)	
CHQ Caseness Scores	0.0142*** (0.000)	0.0266*** (0.000)	0.0097*** (0.0003)	0.0088** (0.0146)	-0.7747*** (0.000)	-0.5133*** (0.000)

p-values are reported between brackets, *** and ** indicate significance at 1% and 5% level.

Table 4. Fixed effects Estimates over Monitoring Stations for Air Pollution Variation per Month and Year

	So$_2$	*O*$_3$	*NO*$_X$	*CO*
Constant	2.110 (0.167)***	33.944 (0.710)***	127.173 (35.692)***	0.839 (0.100)***
February	0.527 (0.264)***	2.138 (1.068)**	8.650 (6.629)	0.084 (0.010)***
March	1.120 (0.359)***	11.228 (1.160)***	-6.734 (7.805)***	-0.388 (0.080)***
April	-0.813 (0.332)***	21.435 (1.663)***	-23.584 (0.446)***	-0.193 (0.049)***
May	-0.530 (0.125)***	21.269 (2.148)***	-30.751 (9.863)***	-0.152 (0.077)**
June	-0.589 (0.282)**	23.298 (1.265)***	-32.773 (8.441)***	-0.185 (0.055)***
July	-0.782 (0.267)***	10.196 (2.442)***	-33.298 (7.581)***	-0.119 (0.052)**
August	- 1.503 (0.719)**	3.245 (1.256)**	28.278 (7.830)***	-0.328 (0.032)***
September	-2.250 (0.785)***	1.162 (0.546)**	-31.780 (12.264)**	0.113 (0.028)***
October	-1.708 (0.757)***	-4.745 (1.319)***	-15.243 (7.881)**	0.013 (0.006)**
November	-1.071 (0.692)	-5.040 (0.931)***	11.064 (5.076)**	0.038 (0.003)***
December	1.545 (0.764)**	-9.598 (0.725)***	53.557 (12.062)***	0.061 (0.004)***

Table 4. (cont.) Fixed effects Estimates over Monitoring Stations for Air Pollution Variation per Month and Year

	So$_2$	*O*$_3$	*NO*$_X$	*CO*
1992	3.548	10.456	19.744	0.078
	(1.618)**	(3.767)***	(4.824)***	(0.016)***
1993	8.228	13.533	21.690	-0.108
	(2.663)***	(3.153)***	(4.925)***	(0.015)***
1994	6.352	8.710	22.627	-0.070
	(3.565)*	(3.780)**	(2.270)***	(0.016)***
1995	7.148	11.127	18.316	-0.092
	(1.646)***	(3.572)***	(2.767)***	(0.017)***
1996	3.192	13.047	33.317	-0.142
	(0.944)***	(2.460)***	(1.338)***	(0.077)**
1997	2.809	9.890	23.564	0.089
	(1.113)**	(1.642)***	(3.278)***	(0.102)
1998	-5.925	1.760	-22.845	-0.193
	(0.924)***	(0.616)***	(3.828)***	(0.095)**
1999	-8.183	12.900	-19.735	-0.172
	(0.789)***	(1.772)***	(4.978)***	(0.103)*
2000	-8.447	12.146	-34.803	-0.291
	(0.995)***	(1.670)***	(4.489)***	(0.101)***
2001	-8.642	5.731	-25.842	-0.251
	(1.101)***	(2.321)**	(3.620)***	(0.101)***
2002	-8.969	8.551	-27.344	-0.411
	(0.951)***	(1.842)***	(3.599)***	(0.099)***
2003	-9.766	-6.385	-36.341	-0.497
	(0.831)***	(1.463)***	(3.508)***	(0.098)***
2004	-11.764	-6.384	-55.772	-0.493
	(0.869)***	(1.359)***	(3.531)***	(0.102)***
2005	-12.840	-12.380	-52.876	-0.526
	(0.755)***	(1.790)***	(3.494)***	(0.104)***
2006	-13.336	-13.272	-56.132	-0.570
	(0.811)***	(1.256)***	(3.587)***	(0.099)***
2007	-13.308	-12.776	-53.969	-0.585
	(0.585)***	(1.212)***	(3.554)***	(0.103)***
2008	-13.705	-11.992	-56.324	-0.604
	(0.620)***	(1.302)***	(3.522)***	(0.104)***
2009	-14.075	-12.732	-57.776	-0.605
	(0.584)***	(2.453)***	(3.475)***	(0.104)***
No. observations	111,617	124,097	173,868	107,247
R squared	0.3452	0.3465	0.2704	0.4333

Standard errors between brackets , *** , ** and ** indicate significance at 1%, 5% and 10% level , the estimates are based on single regressions.

Table 5. Fixed Effects Probit of the Probability o f Moving at Period *t*, Conditional on Characteristics at Previous Period *t-1*.

	So₂	*O₃*	*NOₓ*	*CO*
Air pollutant	0.0097 (0.093)	0.0021 (0.008)	0.0253 (0.0118)**	0.0047 (0.0123)
Household Income	-0.166 (0.036)***	-0.161 (0.035)***	-0.134 (0.032)***	-0.136 (0.036)***
Age	0.151 (0.092)	0.142 (0.087)	0.116 (0.073)	0.094 (0.076)
Average temperature	0.174 (0.071)**	0.121 (0.066)*	0.019 (0.006)	0.090 (0.081)
Wind speed	0.0064 (0.008)	0.0092 (0.008)	0.0151 (0.0078)*	0.0064 (0.0103)
Precipitation	-0.0015 (0.004)	-0.0138 (0.0087)	0.004 (0.007)	-0.006 (0.011)
Household Size	-0.165 (0.026)***	-0.170 (0.025)***	-0.156 (0.025)***	-0.171 (0.033)***
Tenure: owned with mortgage	-0.266 (0.113)**	-0.168 (0.077)**	-0.268 (0.119)**	-0.284 (0.137)**
Poor Health Status	0.043 (0.076)	0.088 (0.122)	0.089 (0.049)*	0.013 (0.022)
Unemployed	0.384 (0.158)**	0.432 (0.151)***	0.397 (0.189)**	0.358 (0.161)**
Marital status: Married	1.270 (0.518)**	0.291 (0.466)	1.195 (0.599)*	0.952 (0.442)**
No. observations	32,791	36,263	43,326	26,559
LR chi-square	1,612.62	1,626.07	1,774.22	1,519.81

Standard errors between brackets, standard errors on wave specific local authority districts
*** , ** and * indicate significance at 1%, 5%, 10% level

Table 6.OLS and Fixed Effects Happiness Regressions using Weekly Averages for Non-Movers and Household Income

	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Model	(1) SO_2	(2) SO_2	(3) O_3	(4) O_3	(5) NO_X	(6) NO_X	(7) CO	(8) CO
Household Income	0.0249 (0.0122)**	0.0241 (0.0135)*	0.0282 (0.0131)**	0.0253 (0.0125)**	0.0243 (0.0076)***	0.0192 (0.0092)**	0.0298 (0.0136)*	0.0258 (0.0126)**
Air pollutant	-0.0031 (0.0005)**	-0.0042 (0.0010)***	-0.0032 (0.0017)*	-0.0068 (0.0033)**	-0.0021 (0.0011)*	-0.0018 (0.001)*	-0.0032 (0.0015)**	-0.0031 (0.0015)**
Age	-0.0111 (0.0018)***	-0.0451 (0.021)**	-0.0095 (0.0015)***	-0.0440 (0.0178)***	-0.0100 (0.0018)***	-0.0308 (0.0167)*	-0.0561 (0.0325)*	-0.0561 (0.0325)*
Age square	1.2e-0.4 (1.8e-0.5)***	5.2e-0.4 (4.0e-0.5)***	9.7e-0.4 (1.4e-0.4)***	6.1e-0.4 (2.6e-0.4)**	1.3e-0.4 (1.1e-0.5)***	3.7e-0.4 (1.7e-0.4)**	5.6e-0.4 (6.0e-0.6)***	5.6e-0.4 (6.0e-0.6)***
Temperature	0.0124 (0.0054)**	0.0126 (0.0055)**	0.0106 (0.0055)*	0.0107 (0.0037)**	-0.0090 (0.0042)**	0.0092 (0.0043)**	0.0221 (0.0113)*	0.0134 (0.0066)**
Temperature square	-1.8e-0.4 (8.1e-0.5)**	-1.6e-0.4 (8.0e-0.5)**	-1.5e-0.4 (7.8e-0.5)*	-1.4e-0.4 (6.2e-0.5)*	-1.2e-0.4 (6.3e-0.5)*	-1.3e-0.4 (6.4e-0.5)**	-3.1e-0.4 (1.6e-0.4)*	-1.8e-0.4 (7.4e-0.5)**
Wind Speed	-0.00036 (0.000019)*	-0.00042 (0.00022)*	-0.00028 (0.00012)***	-0.00032 (0.0001)***	-0.00019 (0.00012)	-0.00021 (0.00011)*	-3.0e-0.4 (1.4e-0.4)**	-0.00015 (0.00007)**
Precipitation	0.0025 (0.0013)*	0.0012 (0.0007)*	0.0016 (0.0009)*	0.0015 (0.0007)**	0.0013 (0.0007)*	0.0013 (0.0006)**	0.004 (0.0022)*	0.004 (0.002)**
Household size	-0.0091 (0.0045)**	-0.0107 (0.0051)**	-0.0114 (0.0041)***	-0.0214 (0.0087)**	-0.0118 (0.0051)**	-0.0321 (0.0214)	-0.0122 (0.0052)**	-0.0234 (0.0106)**
Unemployed	-0.241 (0.027)***	-0.263 (0.046)***	-0.212 (0.032)***	-0.259 (0.049)***	-0.244 (0.029)***	-0.270 (0.044)***	-0.263 (0.034)***	-0.320 (0.049)***
Marital Status married	0.151 (0.101)	0.147 (0.132)	0.292 (0.137)**	0.229 (0.128)*	0.096 (0.051)*	0.122 (0.063)*	0.182 (0.096)*	0.211 (0.118)*
No obs.	56,981	56,981	63,395	63,395	71,467	71,467	48,383	48,383
R square	0.3279	0.3945	0.5111	0.4906	0.3934	0.3895	0.4882	0.4668
MWTP	0.0168	0.0210	0.0225	0.0287	0.0142	0.0123	0.0145	0.0150
MWTP monetary values	£507	£636	£680	£866	£372	£428	£437	£456

Standard errors between brackets, clustered standard errors on wave specific local authority districts, ***, ** and * indicate significance at 1%, 5% and 10% level

Table 7. Happiness Regressions using Weekly Averages

Model	(1)	(2)	(3)	(1)	(2)	(3)
	Panel A: SO_2			Panel B: O_3		
Personal Income	0.0141 (0.0067)**	0.0158 (0.0077)**		0.0151 (0.0068)**	0.0179 (0.0075)**	
Household Income			0.0220 (0.0016)***			0.0288 (0.0101)***
Sulphur Dioxide SO_2	-0.0026 (0.0014)*	-0.0023 (0.0012)*	-0.0035 (0.0014)**	-0.0053 (0.0030)*	-0.0051 (0.0028)*	-0.0069 (0.0039)*
No obs.	65,379	54,793	67,443	72,132	55,065	74,491
R square	0.3879	0.3958	0.3869	0.3944	0.4043	0.3931
MWTP	0.0227	0.0219	0.0222	0.0530	0.0428	0.0291
MWTP monetary values	£372	£300	£660	£708	£588	£864
	Panel C: NO_X			Panel D: CO		
Personal Income	0.0126 (0.0060)**	0.0144 (0.0066)**		0.0158 (0.0088)*	0.0116 (0.0059)**	
Household Income			0.0159 (0.0082)*			0.0193 (0.0105)*
Sulphur Dioxide SO_2	-0.0021 (0.0016)	-0.0020 (0.0019)	-0.0020 (0.0011)*	-0.0027 (0.0014)*	-0.0022 (0.0010)**	-0.0039 (0.0021)*
No obs.	79,215	66,975	81,665	53,475	46,322	55,055
R square	0.3960	0.4079	0.3949	0.4301	0.4417	0.4311
MWTP	0.0248	0.0207	0.0147	0.0310	0.0285	0.0166
MWTP monetary values	£336	£288	£360	£420	£396	£492

Standard errors between brackets, clustered standard errors on wave specific local authority districts

(1) Refers to total sample, (2) refer to non-movers for personal income , (3) Refers to total sample for household income

***, ** and * indicate significance at 1%, 5% and 10% level

Table 8. Robustness Checks Happiness Regressions

Model	SO_2	O_3	NO_X	CO
Panel A1: Monthly averages on air pollutants				
Household Income	0.0241 (0.0124)*	0.0244 (0.0079)***	0.0271 (0.0111)**	0.0212 (0.0115)*
Air Pollutant	-0.0052 (0.0027)*	-0.0070 (0.0029)**	-0.0039 (0.0021)*	-0.0025 (0.0013)*
MWTP monetary values	£857	£960	£537	£471
Panel A2: One day prior to interview air pollutants				
Household Income	0.0178 (0.0103)*	0.0198 (0.0107)*	0.0232 (0.0120)*	0.0373 (0.0132)**
Air Pollutant	-0.0036 (0.0019)*	-0.0027 (0.0051)	-0.0036 (0.0029)	-0.0002 (0.0032)
MWTP monetary values	£458	£513	£643	£27
Panel B1: Within 5 miles from air monitoring station				
Household Income	0.0278 (0.0155)*	0.0330 (0.0147)**	0.0233 (0.0112)**	0.0347 (0.0198)*
Air Pollutant	-0.0047 (0.0011)***	-0.0075 (0.0034)**	-0.0028 (0.0018)**	-0.0041 (0.0017)**
MWTP monetary values	£773	£902	£537	£456
Panel B2: Within 15 miles from air monitoring station				
Household Income	0.0238 (0.0121)**	0.0281 (0.0129)**	0.0184 (0.0109)*	0.0317 (0.0155)**
Air Pollutant	-0.0038 (0.0011)***	-0.0058 (0.0015)***	-0.0024 (0.0013)*	-0.0035 (0.0015)**
MWTP monetary values	£637	£827	£437	£444
Panel C1: Urban Areas				
Household Income	0.0289 (0.0147)*	0.0373 (0.0128)***	0.0242 (0.0114)**	0.0266 (0.0145)*
Air Pollutant	-0.0087 (0.0031)***	-0.0119 (0.0038)***	-0.0039 (0.0021)*	-0.0055 (0.0031)*
MWTP monetary values	£1,201	£1,268	£577	£821
Panel C2: Rural Areas				
Household Income	0.0114 (0.0063)*	0.0181 (0.0079)**	0.0214 (0.0110)*	0.0220 (0.0148)
Air Pollutant	-0.0013 (0.0007)*	-0.0028 (0.0012)***	-0.0025 (0.0032)	-0.0011 (0.0045)
MWTP monetary values	£302	£408	£320	£151
Panel D1: Quadratic term on air pollution				
Air pollutant	-0.0061 (0.0014)***	-0.0088 (0.0034)**	-0.0023 (0.0027)	-0.0004 (0.0027)
Air pollutant square	0.57e-0.4 (0.96e-0.4)	0.0030 (0.00020)	0.14e-0.4 (0.31e-0.4)	-0.0001 (0.0011)
Household Income	0.0222 (0.0101)**	0.0174 (0.0097)*	0.0230 (0.0092)**	0.0267 (0.0112)**

Table 8 (cont.) Robustness Checks Happiness Regressions

Model	SO_2	O_3	NO_X	CO
Panel D2: Quadratic term on income				
Household Income	-0.0087 (0.0361)	-0.0140 (0.0336)	-0.0162 (0.0349)	0.0233 (0.0597)
Household Income square	0.0023 (0.0025)	0.0024 (0.0025)	0.0030 (0.0024)	0.00016 (0.0030)
Air pollutant	-0.0024 (0.0013)*	-0.0067 (0.0032)**	-0.0019 (0.0020)	-0.0020 (0.0011)*
Panel E1: Female				
Household Income	0.0285 (0.0134)**	0.0328 (0.0142)**	0.0198 (0.0595)***	0.0305 (0.0126)**
Air Pollutant	-0.0063 (0.0028)***	-0.0075 (0.0035)**	-0.0019 (0.001)*	-0.0033 (0.0015)**
No obs.	31,831	33,559	36,253	25,596
R square	0.5021	0.5784	0.4983	0.5543
MWTP monetary values	£737	£942	£380	£465
Panel E2: Male				
Household Income	0.0232 (0.0117)*	0.0308 (0.0151)**	0.0175 (0.0439)**	0.0297 (0.0155)*
Air Pollutant	0.0031 (0.0012)**	-0.0062 (0.0026)**	-0.0017 (0.0009)*	-0.0030 (0.0014)**
No obs.	25,150	29,836	35,214	22,787
R square	0.5099	0.6030	0.5061	0.5720
MWTP monetary values	£592	£812	£365	£432
Panel F1: Age 16-24				
Household Income	0.0162 (0.0087)*	0.0138 (0.0073)*	0.0150 (0.0077)*	0.0251 (0.0236)
Air Pollutant	-0.0056 (0.0045)	-0.0050 (0.0037)*	-0.0063 (0.0053)	-0.0023 (0.0014)
No obs.	5,777	7,082	9,616	5,196
R square	0.5239	0.6393	0.5165	0.6142
MWTP monetary values	£703	£761	£380	£197
Panel F2: Age 25-34				
Household Income	0.0450 (0.0215)**	0.0398 (0.0178)**	0.0551 (0.0288)*	0.0219 (0.0115)*
Air Pollutant	-0.0198 (0.0041)***	-0.0106 (0.0044)**	-0.0058 (0.0028)**	-0.0057 (0.0037)**
No obs.	11,627	11,852	13,960	9,880
R square	0.4865	0.6470	0.4783	0.5471
MWTP monetary values	£1,723	£1,032	£410	£860
Panel F3: Age 35-44				
Household Income	0.0535 (0.0224)**	0.0344 (0.0165)**	0.0590 (0.0278)**	0.0329 (0.0143)*
Air Pollutant	-0.0039 (0.0017)**	-0.0105 (0.0042)**	-0.0100 (0.0052)*	-0.0072 (0.0035)**
No obs.	11,697	12,951	13,967	10,431
R square	0.4725	0.5950	0.4581	0.5441
MWTP monetary values	£280	£713	£652	£217

Table 8 (cont.) Robustness Checks Happiness Regressions

Model	SO_2	O_3	NO_X	CO
Panel F4: Age 45-54				
Household Income	0.0212 (0.0102)**	0.0294 (0.0134)**	0.0158 (0.0068)**	0.0636 (0.0317)**
Air Pollutant	-0.0033 (0.0015)**	-0.0063 (0.0034)*	-0.0030 (0.0032)	-0.0102 (0.0085)**
No obs.	11,364	12,051	13,618	10,216
R square	0.4873	0.6168	0.4851	0.5643
MWTP monetary values	£567	£586	£924	£522
Panel F5: Age 55-64				
Household Income	0.0193 (0.0078)**	0.0243 (0.0131)*	0.0202 (0.0086)**	0.0217 (0.0104)**
Air Pollutant	0.0030 (0.0016)*	-0.0033 (0.0020)**	-0.0023 (0.0016)	-0.0022 (0.001)**
No obs.	10,172	10,954	11,277	9,228
R square	0.5105	0.6080	0.4942	0.5744
MWTP monetary values	£441	£806	£353	£498
Panel F6: 65 or older				
Household Income	0.0119 (0.0060)*	0.0156 (0.0078)**	0.0154 (0.0079)**	0.0200 (0.0105)*
Air Pollutant	-0.0006 (0.001)	-0.0128 (0.0069)*	-0.0042 (0.0034)	-0.0012 (0.0045)
No obs.	6,344	8,505	9,029	3,432
R square	0.4321	0.6067	0.4173	0.4934
MWTP monetary values	£434	£1,570	£1,189	£188
Panel G1: Excellent-good health status				
Household Income	0.0249 (0.0119)**	0.0336 (0.0155)**	0.0224 (0.0104)*	0.0231 (0.0126)*
Air Pollutant	-0.0032 (0.0016)**	-0.0056 (0.0018)**	-0.0016 (0.009)*	-0.0017 (0.0035)
MWTP monetary values	£674	£676	£320	£567
Panel G2: Fair-poor-very poor health status				
Household Income	0.0143 (0.0075)*	0.0293 (0.0121)**	0.0183 (0.0096)*	0.0311 (0.0114)**
Air Pollutant	-0.0023 (0.0009)**	-0.0067 (0.0026)**	-0.0040 (0.0019)**	-0.0068 (0.0074)
MWTP monetary values	£347	£869	£483	£302
Panel H1: Smokers				
Household Income	0.0637 (0.0331)**	0.0653 (0.0312)**	0.0636 (0.0253)**	0.0780 (0.0345)**
Air Pollutant	-0.0076 (0.0040)*	-0.0112 (0.0055)**	-0.0070 (0.0047)	-0.0034 (0.0057)
MWTP monetary values	£459	£782	£607	£175

Table 8 (cont.) Robustness Checks Happiness Regressions

Model	SO_2	O_3	NO_X	CO
Panel H2: Non- Smokers				
Household Income	0.0182 (0.0101)*	0.0140 (0.0110)	0.0206 (0.0102)**	0.0241 (0.0101)**
Air Pollutant	-0.0031 (0.0014)**	-0.0022 (0.0011)**	-0.0020 (0.0010)**	-0.0044 (0.0021)**
MWTP monetary values	£760	£1,132	£522	£567
Panel I1: Period 1991-1999				
Household Income	0.0284 (0.0124)**	0.0269 (0.0140)*	0.0260 (0.0118)**	0.0366 (0.0136)*
Air Pollutant	-0.0064 (0.0021)***	-0.0139 (0.0069)**	-0.0031 (0.0015)**	-0.0103 (0.0056)*
MWTP monetary values	£885	£1,672	£489	£1,011
Panel I2: Period 2000-2009				
Household Income	0.0246 (0.0106)**	0.0280 (0.0158)*	0.0260 (0.0129)**	0.0231 (0.0126)*
Air Pollutant	-0.0039 (0.0018)**	-0.0023 (0.0012)*	-0.0021 (0.0011)**	0.0017 (0.0035)
MWTP monetary values	£609	£467	£307	£271
Panel J1: High Pollution Areas				
Household Income	0.0391 (0.0193)**	0.0341 (0.0158)**	0.0235 (0.0123)*	0.0285 (0.0228)
Air Pollutant	-0.0054 (0.0024)**	-0.0103 (0.0047)**	-0.0038 (0.0021)*	-0.0028 (0.0025)*
MWTP monetary values	£546	£982	£571	£364
Panel J2: Low Pollution Areas				
Household Income	0.0329 (0.0189)**	0.0277 (0.0180)*	0.0181 (0.0093)*	0.0317 (0.0191)*
Air Pollutant	-0.0036 (0.0020)**	-0.0075 (0.0035)**	-0.0026 (0.0012)**	-0.0015 (0.0029)
MWTP monetary values	£445	£677	£537	£326
Panel K1: Life satisfaction regressions for non-movers				
Household Income	0.0206 (0.0123)*	0.0255 (0.0117)**	0.0235 (0.0105)**	0.0231 (0.0126)*
Air Pollutant	-0.0039 (0.0009)***	-0.0046 (0.0021)**	-0.0029 (0.0013)**	-0.0033 (0.0012)**
No obs.	39,915	45,827	56,758	39,348
R square	0.6027	0.6067	0.6131	0.6380
MWTP monetary values	£607	£713	£401	£474
Panel K2: CHQ “Caseness Scores” regressions for non-movers				
Household Income	-0.1639 (0.0473)***	-0.1012 (0.0439)**	-0.1415 (0.0428)***	-0.1488 (0.0439)**
Air Pollutant	0.0264 (0.0122)**	0.0225 (0.0122)*	0.0141 (0.0073)*	0.0172** (0.0065)
No obs.	62,183	66,587	75,675	50,823
R square	0.5062	0.5864	0.5022	0.5620
MWTP monetary values	£643	£875	£396	£462

Standard errors between brackets, clustered standard errors on wave specific local authority districts
***, ** and * indicate significance at 1%, 5% and 10% l

Table 9. Arellano-Bond Happiness Regressions

Model	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Panel A: SO_2				Panel B: O_3			
Lagged Happiness	0.048 (0.008)***	0.0444 (0.0085)***	0.052 (0.0078)***	0.049 (0.0084)***	0.058 (0.0077)***	0.059 (0.0083)***	0.059 (0.0075)***	0.061 (0.0081)***
Personal Income	0.0169 (0.0096)*	0.0172 (0.0100)*			0.0208 (0.0090)**	0.0190 (0.0094)**		
Household Income			0.0209 (0.0104)*	0.0259 (0.0113)**			0.0225 (0.0104)**	0.0261 (0.0146)*
Sulphur Dioxide SO_2	-0.0054 (0.0028)*	-0.0052 (0.0029)*	-0.0063 (0.0028)**	-0.0057 (0.0028)**	-0.0048 (0.0025)*	-0.0042 (0.0023)*	-0.0056 (0.0031)*	-0.0054 (0.0030)*
MWTP	0.0480	0.0455	0.0392	0.0307	0.0345	0.0331	0.0353	0.0313
MWTP monetary values	£642	£623	£1,152	£927	£461	£453	£1,037	£945
No obs.	33,670	28,920	34,791	29,898	37,028	32,004	38,263	33,087
Wald chi-square	39,244.05	37,289.21	39,734.42	37,713.20	44,913.80	42,370.66	45,425.43	42,724.34
Arellano-Bond test for AR(2) in first differences	0.240	0.372	0.442	0.616	0.784	0.772	0.783	0.776
Exogeneity test	0.136	0.095	0.356	0.179	0.251	0.318	0.394	0.334
	Panel C: NO_X				Panel D: CO			
Happiness with one lag	0.065 (0.0070)***	0.063 (0.0075)***	0.068 (0.0069)***	0.068 (0.0074)***	0.047 (0.0094)***	0.051 (0.0099)***	0.054 (0.0092)***	0.058 (0.0098)***
Personal Income	0.0148 (0.0060)**	0.0162 (0.0062)***			0.0165 (0.0106)	0.0124 (0.0110)		
Household Income			0.0155 (0.0085)*	0.0138 (0.0098)			0.0186 (0.0154)	0.0088 (0.0165)
Sulphur Dioxide SO_2	-0.0017 (0.0012)	-0.0016 (0.0012)	-0.0020 (0.0011)*	-0.0018 (0.001)*	-0.0010 (0.0029)	-0.0015 (0.0030)	-0.0014 (0.0029)	-0.0019 (0.0030)
MWTP	0.0161	0.0149	0.0117	0.0121	0.0290	0.0180	0.0153	0.0161
MWTP monetary values	£215	£204	£344	£365	£388	£247	£450	£486
No obs.	44,915	38,259	44,326	38,885	27,749	23,664	28,559	24,369
Wald chi-square	54,002.94	51,507.59	54,589.65	52,008.40	38,655.60	36,510.01	38,918.38	36,805.40
Arellano-Bond test for AR(2) in first differences	0.813	0.849	0.852	0.807	0.412	0.325	0.475	0.284
Exogeneity test	0.098	0.083	0.212	0.162	0.054	0.068	0.123	0.135

Standard errors between brackets, clustered standard errors on wave specific local authority district (1) Refers to total sample and (2) refer to non-movers for personal income, (3) Refers to total sample and (4) refer to non-movers for household income, ***, ** and * indicate significance at 1%, 5% and 10% level

Table 10. Latent Class Ordered Probit Regressions for Non-Movers

Model	Ordered probit	Latent class generalized ordered probit model		
		Class 1	Class 2	Class3
		Panel A: SO_2		
Household income	0.0460	0.0507	0.0494	0.0173
	(0.0082)***	(0.0257)**	(0.0266)*	(0.0100)*
Sulphur Dioxide (SO_2)	-0.0053	-0.0128	-0.0028	-0.0022
	(0.00011)***	(0.0075)*	(0.0013)**	(0.0026)
MWTP monetary values	£607	£1,399	£403	£260
No. observations	49,270			
LR chi-square	2,915.71		3,150.17	
	[0.000]		[0.000]	
		Panel B: O_3		
Household income	0.0345	0.0425	0.0522	0.0342
	(0.0157)**	(0.0178)**	(0.0125)**	(0.0117)***
Ground Level Ozone (O_3)	-0.0068	-0.0070	-0.0077	-0.0062
	(0.0032)*	(0.0022)***	(0.0033)*	(0.0026)***
MWTP monetary values	£751	£542	£895	£616
No. observations	56,768			
LR chi-square	2,937.92		3,116.31	
	[0.000]		[0.000]	
		Panel C: NO_X		
Household income	0.0221	0.0313	0.0129	0.0223
	(0.0101)**	(0.0149)**	(0.0066)**	(0.0058)***
Nitrogen Oxides (NOX)	-0.0022	-0.0032	-0.0022	-0.0025
	(0.0011)*	(0.0013)**	(0.0009)**	(0.0009)***
MWTP monetary values	£365	£236	£582	£332
No. observations	68,982			
LR chi-square	3,995.21		4,397.20	
	[0.000]		[0.000]	
		Panel D: CO		
Household income	0.0230	0.0344	0.0146	0.0288
	(0.0104)**	(0.0145)**	(0.0053)***	(0.0137)**
Carbon Monoxide (CO)	-0.0033	-0.0040	-0.0020	-0.0031
	(0.0015)**	(0.0022)*	(0.0009)**	(0.0012)**
MWTP monetary values	£468	£537	£523	£482
No. observations	47,660			
LR chi-square	2,222.16		2,588.12	
	[0.000]		[0.000]	
Membership class		2.96%	10.33%	71.41%

Standard errors between brackets, p-values between square brackets
***, ** and * indicate significance at 1%, 5% and 10% level.

CONCLUSIONS

The first chapter examined the effects of voluntary program “Clean Air Works” in counties located in Charlotte Area of North Carolina State. The first concluding remark is that the quadruple DID results show a significant reduction in actual ozone levels when the “Clean Air Works” project is implemented in the treatment group. Secondly, the estimates show that the difference in the ozone levels between the treatment and control group is reduced, when the smog alerts and the change in the threshold from 80 ppb to 75 ppb are associated with the program. The results are robust and valid as the common trend assumption hypothesis is accepted. As policy makers discuss ways to improve environmental quality, the adoption of voluntary programs, such as “Clean Air Works” program, might be potentially an efficient mechanism. This program can be a lesson and example for improving air quality that can be applied in other US areas. Local and regional governments in collaboration with air quality boards and chambers of commerce can follow the practices and incentives of the “Clean Air Works” program. Tax-free benefits for the employee and employer using public transit, teleworking, offering flextime and alternative work schedules, subsidies and free parking for vanpoolers and carpoolers are some of the practices that can be applied in order to improve air quality. Moreover, energy efficiency management, such as the use of construction equipment and small diesel generators for evenings and reschedule of lawn maintenance during the smog alert days and implementation of energy conservation plans are other useful practices which reduce air pollution.

The second chapter tried to answer in three main questions. Firstly, it examined the effects of the vanpool program on traffic volume, which has been implemented in York County of South Carolina State. Secondly, it explored whether individuals change their behaviours when a smog warning is issued in York and Spartanburg Counties in South

Carolina and whether these alerts are effective under the vanpool program regime. Finally, the effects on the ozone levels coming from the change of the warning threshold from 80 ppb to 75 ppb, which took place in 2008, are established. A quadruple DID approach was followed. The findings suggest that the vanpool leads to a reduction of 800 cars a day, resulting to ozone reduction by 0.00412 ppb. The DID estimates are valid considering the parallel trend assumption which is accepted. Concluding, the policy implications and incentives of the vanpool program applied in York County can be extended in other areas of South Carolina State and other US States, especially in "non-attainment" areas. As it has been discussed, monthly subsidies, free parking to employees using vanpooling and gas card subsidies for vanpool drivers are few of the incentives than can be followed.

The third chapter differs from the two first and negotiated the effects of recycling on air pollution. The environmental problems of landfills are difficult issues to fix. As more waste is put into landfills, the bigger the problem gets. Especially, products that are slow to decompose can remain in landfill sites for long time, even for centuries, often emitting air pollutants that could be harmful to the environment and public health. Thus, the air pollution emitted can produce both long- and short-term adverse health effects, including bronchitis, headaches, heart disease and cancer. Motivated by this problem, the third chapter examined the relationship between $PM_{2.5}$ air pollutant and recycling rate in Massachusetts State. A negative relationship between $PM_{2.5}$ and recycling rate has been found indicating that recycling can lead to air quality improvement. The results show that one per cent increase in recycling rates can lead to reduction of $PM_{2.5}$ at 0.0018 micrograms per cubic meter ($\mu g/m^3$). Recycling is just one of many ways that can improve the air quality. Also recycling decreases the need for raw materials and reduces the demand for power preserving natural resources for the future. Collecting, processing and shipping recycled materials to industrial users require less energy than mining, refining, processing and shipping raw materials. Thus, state and federal identification, which supports and provides incentives for pollution prevention and recycling, will allow getting everyone involved and they will help to produce a better environment for many generations to come.

In the fourth chapter the effects of air pollution on self-reported well-being happiness have been examined. Highly disaggregated spatially data from the British Household Survey have been used. The results showed that the monthly MWTP is varied among the air pollutants examined. More specifically, for sulphur dioxide and ground-level ozone the MWTP ranges between £636-£660 and £780-£864 per year, while the MWTP values for carbon monoxide and nitrogen oxides range between £456-£492 and £372-£360 per year respectively. The estimates are robust to a variety of model specifications and models, such as Probit fixed effects and GMM. In addition, regressions took place among various sub-samples, including gender, age groups, individuals with poor and health status and different periods.

In addition, this chapter aimed to fill the gap in the literature regarding the heterogeneous effects of income and air pollution on well-being. In particular the question is whether or not the unobserved individual heterogeneity in the data set is accounted for makes only small differences to the point estimates but may result in large differences when one ignores the slope heterogeneity in well-being equations. For this reason the latent class random effects generalized ordered probit model has been applied. The results show that there is slope heterogeneity in the happiness equations, where the least satisfied classes are willing to pay more for a reduction in air pollution. The findings suggest that increases on income are associated with higher probabilities of reporting high levels of happiness while reductions on air pollution decrease the probability of reporting a low level of happiness.

The importance of this study comes from the fact that the analysis relies on detailed micro-level data, using grid references, instead of using electoral divisions, cities, counties or countries like other studies, as well as more advanced econometric techniques, such as dynamic panel, latent class model estimation, which allow for heterogeneity in the effect. Generally, the results show that the life satisfaction approach contains very useful information on individuals' preferences and at the same time expands the economic tools in the area of non-market evaluation. However, this study is not without limitations, as the drawbacks of the LSA have been extensively discussed.