Air Quality Management Areas and Pollution – Evidence from the UK

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Abstract

This paper investigates the effect of air quality management areas (AQMAs) - local, non-binding commitments to improve air quality - on pollution levels in the United Kingdom. I exploit the staggered declaration of the policy which is triggered when a local authority marginally and temporarily exceeds national air quality benchmarks. The institutional setting thus creates a natural control group, namely local authorities with pollution levels just below the thresholds for the time being. The difference-in-differences estimation suggests that AQMAs fail to lead to decreases in average NO_2 concentration and the number of days on which daily NO_2 limits are exceeded.

Keywords: Air Quality Management Areas; Monitoring Stations; Air Pollution; Exceedance; Difference-in-Differences

1 Introduction

Air pollution has long been regarded as a substantial health issue. Every day 1.8 billion children worldwide breathe highly polluted air that puts their health and development at serious danger (WHO et al., 2018). Low ambient air quality is caused by multiple sources, mainly, by the combustion of fossil fuels, power plants, greenhouse gas emissions, and industrial activities and facilities. Transportation - a major use of energy - contributes, too, to air pollution and to global warming.

Good air and natural environment quality foster good health (Lovell et al., 2018). Public health is determined by the way people live and, broadly, by the aspects of their daily life. This includes social and economic dimensions, in addition to the quality of the environment they live in. Across Europe, human activities cause a significant burden of illness that is attributed to the exposure of low air quality.

In the European Union (EU), environmental factors such as low air quality and certain weather conditions including high temperature, frequent heavy rains, and floods and droughts are considered as key risk factors causing death (OECD, 2018). In 2012, air pollution was responsible for 630 000 deaths in the 28 Member States of the EU (EU-28) according to data from the WHO (WHO et al., 2016). This number, however, decreased to around 400 000 premature deaths in 2018 (EEA, 2020). In the United Kingdom (UK) – the subject of this study - many local authorities and cities have regularly breached the recommended threshold of air pollution set by the national government. The health burden of low air quality is substantial; in the UK alone, about 307,000 life-years are lost every year and air pollution contributes to about 30,000 premature deaths (Gowers et al., 2014).

In addition to adverse health effects, pollution also carries substantial economic and financial consequences. This usually happens through several channels; shortening lives, increasing deaths and migration, therefore affecting the working population size; increasing the number of lost working hours and days due to illness and absenteeism; lowering productivity at work; and affecting the natural capital. In Europe, the rise in air pollution levels leads to substantial reductions in output per capita, hence in economic activity. It is estimated that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentration causes a 0.8% reduction in real GDP annually (Dechezlepretre & Stadler, 2019). Knowing that the EU's GDP in 2017 was about EUR 15 trillion[1], this means that curbing air pollution would increase the EU's GDP by 0.8%, or by EUR 120 billion annually in the short run.

Air pollution affects the UK economy considerably. It drains about £20 billion each year from the economy (Hodges, 2018). Recent research indicates that in 2017 alone, the costs of air pollution to the National Health Service (NHS) and social care in England were £157 million and that these costs could rise to as much as £18 billion by 2035 if the issue is not addressed (Pimpin et al., 2018).

Investing in certain integrated policies that support cleaner energy consumption and production, energy efficiency, and cleaner passenger vehicles is regarded as an effective option to eliminate or at least to reduce key sources of air pollution. Policies that aim to reduce air pollution and to protect the environment offer a win-win situation for both the public and the environment. These policies reduce the burden of air pollution-related diseases and simultaneously contribute to the mitigation of climate change.

Policymakers have started to tackle this problem by taking several actions. In the EU, policymakers have considered air pollution as one of the most significant environmental problems. Since the begging of 1980s, several EU directives have set air pollution limit values and target values for different pollutants. The most recent EU's air quality directive is the Directive on Ambient Air Quality and Cleaner Air for Europe. This directive was adopted in 2008 and it consolidated a series of previous directives such as the Directive 96/62/EC on ambient air quality assessment and management ("the Air Framework Directive"). Basically,

[1]EU's GDP statistics can be found on this website:`shorturl.at/hzDM6`.

this Directive aims to maintain a good quality of ambient air. However, its objectives are also to define the fundamentals of a common strategy to improve air quality and protect human health and the environment, to assess ambient air quality among Member States according to common standards, and to collect adequate information on air quality and make it accessible by the public.

In response, the UK government announced the National Air Quality Strategy (Department of the Environment, the Scottish Office and the Welsh Office, 1997). It includes the UK Air Quality Objectives (AQOs) which comply with the EU limit and target values. This piece of legislation has a strong local component in which local authorities are obliged to review and assess the air quality within their territories on a regular basis. For example, due to the recognised adverse health impacts of air pollution exposure both the EU and the UK mandate that nitrogen dioxide (NO_2) concentrations are to remain below an annual mean of 40 μg$/m^3$; in addition, an hourly mean of 200 μg$/m^3$ must not exceed more than 18 times in a given year (European Communities Council Directive, 1999). Local governments who find that pollution levels have exceeded one of these thresholds are obliged to take counter-measures and to prepare Air Quality Action Plans (AQAPs). The AQAPs follow the declaration of designated Air Quality Management Areas (AQMAs) that are areas of the respective local authority in which counter-measures are focused.

While the pollution thresholds are binding in that they automatically trigger AQMAs, local authorities have substantial leeway in what measures they take to tackle pollution and how they design their respective AQMAs. Typically, they develop air quality action plans (AQAPs) that are focused on public transport improvements and traffic emissions reduction. Moreover, the time period for which counter-measures remain in place varies considerably between local authorities depending on the complexity of the options chosen (NSCA, 2001). There are also no explicit penalties or centralized reduction schedules set by the UK government. This raises the question of whether AQMAs - more than 700 of which have been declared across the UK - pay more than lip-service to the goal of pollution reduction and have actually been effective. This is precisely the main objective of this study.

Figure 1 shows the areas across the UK that are covered by declared AQMAs. There is no size requirement for AQMAs. However, AQMA boundaries should cover the areas where an exceedance has first been detected and where air quality is thus likely to be low. Local authorities have taken individual approaches and different methods for setting the boundaries of their AQMAs. While some local authorities have chosen an approach where a "hot-spot" is declared as an AQMA, others declared AQMAs that covered whole boroughs.

My identification strategy exploits the staggered declaration of AQMAs in a difference-in-differences setting. **Figure** 2 illustrates the process of the declaration of an AQMA. The timing of an AQMA declaration is determined by the marginal exceedances of air quality thresholds. As a result, local authorities that follow very similar pollution trends will declare AQMAs at different points in time. **Figure** 3 illustrates the intuition by plotting annual mean NO_2 concentrations for three local authorities. Between 1997 and 2012, all three local authorities follow similar time trends close to the annual mean of 40 $\mu g/m^3$ threshold but never exceeding it. However, in 2013 Newcastle slips across the threshold and thus had to declare an AQMA, the same happens to Stoke-on-Trent in 2016. In a two-local-authorities case, Stoke-on-Trent would serve as the counter-factual for Newcastle. Obviously, this can be extended to all the 125 local authorities that obtain pollution measures whereby I distinguish between local authorities that have adopted at some point in time and those that have never adopted. Never-adopters may or may not be a good control group. In **Figure** 3, Brighton-Hove never quite breaches the limit but - at least until 2010 - follows reasonably similar pollution trends. In practice, it turns out that including such non-adopting local authorities in the control group has little impact on the estimated effects. To overcome concerns regarding the inappropriate control group and as a robustness check, I re-run all specifications only using local authorities that have declared AQMAs at some point in time ("ever-adopters").

To the best of my knowledge, this study is the first to provide a comprehensive empirical analysis of the effect of the air quality management areas on air quality. There is a substantial interest among policymakers regarding the effectiveness of AQMAs. As such I make an important contribution by providing evidence for whether this piece of UK flagship legislation has been successful in improving air quality. The findings suggest that – similar to many other local approaches such as congestion charges, driving restrictions, and low emission zones – AQMAs have failed to lead to substantial improvements in air quality. The estimates are precise enough to rule out any substantial air quality improvements in either the short-run or the long-run.

The remainder of this paper is structured as follows: Section **2** provides additional background information on AQMAs and also provides an overview of the effectiveness of other local measures aimed at tackling air pollution. Section **3** describes the data and provides descriptive statistics. Section **4** provides the empirical framework with a focus on key identifying assumptions. Section **5** presents the results and several robustness checks. I discuss and conclude in Section **6**.

2 Background

In urban places, passengers and pedestrians spend significant time in close proximity to or indeed inside of vehicles, and thus exposed to air pollution from NO_2 and other pollutants (Molle et al., 2013). Crowded sidewalks coincide often with traffic congestion, most frequently in major cities where pedestrian paths are adjacent to streets.

2.1 Air Quality Management Areas

The main purpose of declaring AQMAs is the mitigation of emissions from diesel and motor vehicles which emit NO_2, particulate matter (PM_{10} & $PM_{2.5}$), sulfur dioxide (SO_2) and carbon monoxide (CO). Road transport is the largest source of NO_2 emissions in the UK affecting human health as NO_2 inflames the airways in the lungs and, in the long-run, affects how well our lungs work - especially for children, elderly people and asthma patients (Air Quality Expert Group, 2004).

AQAPs are considered as an essential Local Air Quality Management (LAQM) component (Department of Environment Food and Rural Affairs, 2013) as they provide local authorities with the mechanism to state their intentions to meet the AQOs (NSCA, 2000). Since emissions from road vehicles are likely to be the triggering factor for most of the declared AQMAs, the action plans entail transport-related measures executed by local authorities. Local authorities are free to choose the exact measures they want to adopt. Typically, AQMAs are areas in which additional investment into public transportation is made, bike lanes are being built, air quality warnings go up, multiple occupancy lanes and car-pooling schemes are designed, etc...

Many of these measures have been trialled by various local governments across the UK. Road pricing initiatives such as small- or large-scale pilot schemes - in which motorists are charged if they enter a specific zone - have been implemented in Bristol, Cambridge, Leicester, Edinburgh and Leeds in order to reduce vehicle movements. Furthermore, several local authorities have undertaken random vehicle emissions testing schemes. This means that the local authority can test vehicles at the roadside and issue penalties to drivers whose vehicles fail emission tests (Elsom et al., 2000). Other measures such as the parking levies give the local authority discretionary powers to dis-incentivize driving and the provision of workplace parking (Beattie et al., 2000).

The implemented action plans following an AQMA's declaration often follow a similar blueprint across local authorities, especially when they are located within the same region and when they breach the threshold of the same pollutant, which puts similar challenges in front of local authorities. However, strategic planning is an evolutionary process that takes into consideration changes in circumstances and air quality over time. Therefore, a periodic review and assessment process can lead to changes in the action plans reflecting locality-specific circumstances and implemented by each local authority (Beattie et al., 2000).

2.2 Low Air Quality: Potential Effects

The main concern of environmental policies is human health. Principally, the motivation for these policies is to protect people against risky exposure to pollution in the environment where they live and work. Besides retaining human health, the establishment of environmental policies considers other integral concerns related to economic growth, industry, trade, transportation, and energy.

Our understanding of the relationship between environment and public health comes from toxicology and epidemiology in the health science literature. So far, economists have made significant contributions to this topic. On the one hand, the economics literature examines the relationship between environmental degradation and public health among other related outcomes (labor productivity, human capital, welfare, economic costs, etc...), and on the other hand, it questions the effectiveness of certain environmental policy measures – such as air quality policy – in curbing air pollution.

2.2.1 Public Health

Many studies have documented the relationship between air pollution and health outcomes. Chay & Greenstone (2003) used a quasi-experimental research approach to examine the relationship between infant mortality and pollution. Their study exploited differential variations in total suspended particulates (TPSs) across different counties and sites in the US caused by the 1981-1982 recession. They found that reducing pollution decreases infant death rates at the county level, suggesting that reducing TPSs by 1 $\mu g/m^3$ results in 4-7 fewer deaths per 100,000 live births. Currie et al. (2009a) examined the impact of air pollution on infant health. The authors obtained information about the exact addresses of mothers and information on air quality levels in New Jersey in the 1990s. Mothers were selected based on the proximity to monitoring stations in addition to accounting for maternal fixed effects. Currie et al. (2009a) concluded that mothers' exposure to pollution, especially CO, has negative effects both during and after birth. Particularly, the estimates showed that exposure to CO increases the likelihood of low birth weight by 8% and the likelihood of infant mortality by 2.5%.

Janke (2014) studied the impact of air pollution on children aged 5–19 years in England. She compiled information on daily hospital emergency admissions and pollution levels of NO_2 and ozone O_3, and combined this information with air pollution warnings data to measure the effect of avoidance behavior caused by air quality alerts released by local governments in the UK. Only when controlling for avoidance behavior the results were statistically significant. Janke (2014) found that children's admissions to hospital due to respiratory problems has increased by 0.1% as a result of a 1% increase in NO_2 or O_3 concentrations. Fan et al. (2020) examined the relationship between heating and air pollution and the latter's impact on health across several Chinese cities from 2014 to 2015. The method they used was a regression discontinuity design based on the effect of air pollution on mortality levels around the turning-on dates of the heating systems in 114 northern Chines cities. The estimates suggested that heating in winter leads to deterioration in the Air Quality Index (AQI) by a 10-point increase which causes overall death rates to increase by 2.2%.

Transportation pollution is known worldwide as a major source of air pollution which also affects public health among other economic indicators. Schlenker & Walker (2016) benefited from the large variation in daily air pollution levels caused by daily airport congestion measured as the amount of time planes spend idling on the tarmac. They demonstrated that daily congestions on airport runway lead to significant increases in local pollution in California. More importantly, their estimates showed that one standard deviation in daily pollution levels results in an increase in hospitalization costs by $1 million for people living close to the twelve largest airports in California. Using a generalized difference-in-differences model, Bauernschuster et al. (2017) documented that higher traffic volumes caused by strikes in public transportation in Germany have led to increases in air pollution by 14%, which in turn caused an 11% increase in hospital admissions for respiratory diseases among young children. Based on a natural experiment, and exploiting the dispersion of cheating diesel cars and the rapid spread of these cars - which offers a reasonable external variation of the exposure to pollution across the United States - Alexander & Schwandt (2019) found that cheating diesel cars (polluting cars) affect both air quality and public health. Precisely, their estimates revealed that the increase in cheating diesel cars in the US from 2008 to 2015 has led first, to a 2.0% increase in AQI for $PM_{2.5}$, second, to a 1.9% increase in low-birth-weight rates, and third, to an increase in the number of visits to asthma emergency department among children.

2.2.2 Human Capital and Labour Productivity

Economic research has expanded the scope of analyzing the impact of environmental pollution beyond traditional health outcomes. Health shocks caused by environmental factors can affect the economy through direct effects on human capital and productivity.

Outdoor air quality is a major environmental health problem that affects - among other health outcomes - cognitive performance. Currie et al. (2009b) studied the impact of pollution on attendance in elementary and middle schools in Texas. They obtained administrative data on schooling attendance and information about air quality. The authors adopted a triple difference-in-differences (DDD) strategy; they controlled for average period-by-year effects across all schools to guard against further unobserved differences by period and year, and considered differential changes in pollution levels within school-year-period cells. Their results showed that the increase in CO levels raises absences. As for those who attend and present at schools, Zweig et al. (2009) found that air pollution affected their performance adversely. Zweig et al. (2009) used school fixed effects to study the effect of student's exposure to outdoor pollution. They combined data on individual-family, air pollution, and standardized test scores by grade, school, and year in California. The results suggested that a 10% decrease in $PM_{2.5}$ increases math test scores and reading scores by 0.14% and 0.21%, respectively.

Exposure to air pollution can affect people's ability to work productively, often through illness and absenteeism. Graff Zivin & Neidell (2012) studied the effect of air pollution exposure on the productivity of farm workers. The authors used a panel data set of daily worker output in the agricultural sector in California, where farm workers were paid through piece rate contracts. The results suggested that at levels well below federal air quality standards, a 10 ppb drop in O_3 concentrations raises worker productivity by 4.2%. Hanna & Oliva (2015) exploited the exogenous variation in air pollution levels caused by the closure of a refinery in Mexico City on March 18, 1991, to estimate the impact of air pollution reduction on the number of hours worked. The closure aimed to reduce pollution levels as the refinery represented about 35% of the total refining capacity in Mexico. The refinery closure benefited the workers in the neighborhoods located within a 5 km radius of the refinery relative to those that were farther away. The results showed that a 20% drop in SO_2 led to a 1.3-hour increase in hours worked the following week after the closure. In addition, pollution reduction led to monetary gains throughout the year for workers who lived near the refinery (480 Peso or USD 126).

He et al. (2019) examined the effect of the exposure to pollution on worker output at two manufacturing sites in China. To investigate the short-term impacts of the variation in air pollution levels on daily productivity levels, He et al. (2019) used daily output records of workers at the two manufacturing sites who are paid according to how much each worker produce daily. They found that a worker output shortfall by 0.5 to 3% is associated with his/her exposure to an equivalent of 10 $\mu g/m^3$ $PM_{2.5}$ during a period of 3-4 weeks preceding the day of production. In a recent study, Chang et al. (2019) estimated the impact of pollution on white-collar labor in China. Particularly, they used data on the daily productivity of call-center workers in Shanghai and Nantong. Their firm-level analysis showed that air pollution has a statistically significant negative effect on workers' productivity. Precisely, the number of daily calls handled by a worker dropped on average by 0.35% as a result of an increase by 10-unit in the air pollution index (API).

While most previous research has focused on outdoor pollution, there is also a nascent literature that analyses the effects of indoor pollution, in particular on schooling outcomes. Several studies have examined the impact of indoor air quality (IAQ) on academic performance and found that students performed better due to IAQ-renovations such as remediation, ventilation, and roof projects (Smedje & Norback, 2000, Haverinen-Shaughnessy et al., 2011, Bakó-Biró et al., 2012, Stafford, 2015).

2.2.3 Well-being and Violence

Air quality is also associated with people's subjective well-being. Luechinger (2009) assessed the impact of air pollution on individuals' well-being in Germany by combining individual-level large panel survey and high-resolution SO_2 data in a difference-in-difference and instrumental variable approach. The identification strategy departs from a natural experiment that exploits the obligation to install scrubbers at power plants, where treatment and control counties are determined by wind direction. In addition, the author used housing hedonics (rental prices) to calculate the willingness to pay for good air quality. The results showed that SO_2 concentration negatively affects both life satisfaction (with larger estimates for the instrumental variable specification) and rents.

Luechinger (2010) investigated the impact of SO_2 pollution on life satisfaction in Europe between 1979 and 1994. In addition to SO_2, he obtained data on household income, and on life satisfaction at the individual level from a cross-section survey in EU member states and Norway. The author used an instrumental variable approach where he instrumented the home-country pollution level with trans-boundary air pollution caused by foreign-countries' emissions. The conventional estimates showed that the willingness-to-pay was inversely affected by air pollution, while the instrumental variable method doubled the willingness-to-pay estimates.

Levinson (2012) relied on the US General Social Survey (GSS) and pollution data to show how air quality affects individuals' happiness. The author showed that, on the one hand, a lower level of happiness was reported when respondents were interviewed on days with low air quality. On the other hand, he showed that wealthy people reported higher levels of happiness. Therefore, there is a trade-off between air quality and income levels. Moreover, on a three-point scale, the estimates suggested that a 10 g/m3 increase in air pollution results in a reduction in happiness of 0.014, while an increase of annual income by 10% causes an increase of happiness of 0.013. Ferreira et al. (2013) investigated the relationship between air pollution and welfare using spatially disaggregated European regional data on ambient air pollution concentrations (SO_2) and other spatial variables to control for climate and several economic indicators. As for the welfare variable, the authors used the European Social Survey (ESS) survey data that were collected between 2002 and 2007. The results from the ordinary least squares (OLS) estimation revealed that, on an 11-point life satisfaction scale, a 1 $\mu g/m^3$ increase in SO_2 concentrations reduces life satisfaction by about 0.016 to 0.030 points.

Exposure to air pollution can impose critical costs on societies and can lead to a rise in violent crimes. (Herrnstadt et al., 2016) examined the causal relationship between crime and pollution in Los Angeles and Chicago in a difference-in-differences specification. The authors compared crime rates in two regions in Los Angeles on treated days with winds blowing from the sea with dirty air, to untreated days when there was no wind blowing to that area. They found that on treated days, the rate of crime was 6.1% higher than that on untreated days compared to control neighborhoods. (Herrnstadt et al., 2016) replicated the same strategy for Chicago and compared the impact of air pollution on crime rates on opposite sides of the interstate free highway (I-290). The intuition is as such: on days when the wind blows from the south, interstate pollution affects the northern areas to the road and vice versa. Therefore, the side of the road from which the wind blows acts as a control. The results also suggested a positive relationship where crime rates increased by 2.2% on treated days.

Lu et al. (2018) used two different approaches to assess the relationship between air pollution, and criminal activity and unethical behavior at the city-level between 1999 and 2009. The first approach was based on fixed-effects Poisson regression models via maximum likelihood estimation. The results of a 9-year panel of 9,360 cities in the US showed that air pollution predicted major crime categories. The second approach was based on three controlled experiments in the US and in India. The findings identified that anxiety is the mechanism that explains the relationship between pollution and unethical behavior. Burkhardt et al. (2019) obtained data on daily crime rates, air pollution, and climate from 2006 to 2013 in the US to study the short-term impact of $PM_{2.5}$ and O_3 exposure on crime commission and found that air pollution increased violent crimes, particularly, aggressive behavior. The poisson quasi-maximum likelihood results revealed that air pollution increases violent crimes, especially assaults. (Bondy et al., 2020) investigated the effect of ambient air pollution exposure on crime in London for the years 2004-05. The authors used panel administrative data to estimate models with ward fixed effects and used wind direction to instrument local air pollution concentrations. The bottom line is that exposure to elevated levels of air pollution leads to higher crime rates. The findings suggested that an additional 10 AQI points leads to an increase in crime rate by 0.9%.

2.3 Low Air Quality: Policy Measures

Local government measures to tackle air pollution can be broadly divided into two categories: market-based interventions and command-and-control measures where the restrictiveness of the controlling element varies. Many local governments focus on policies and regulations related to traffic and road transport air pollution. A popular market-based policy is congestion charging schemes (CCSs). London has been one of the pioneers of such a scheme in Europe. Currently, London drivers pay £11.50 (up from £5 when it was introduced in 2003) in order to enter the city center. Early evaluations of the policy showed that it was effective in reducing air pollution. Total emissions of NO_2 and PM_{10}, in the charging zones decreased by 12% and 11.9% respectively (Kelly et al., 2011). It also improved traffic flows and reduced inbound traffic (Leape, 2006). Recent evidence is more mixed. Atkinson et al. (2009) concluded that there were no overall changes in pollution concentration associated with the introduction of the scheme. However, background monitors suggest a reduction in some pollutants – such as NO_2, PM_{10} and CO - in areas covered by the scheme relative to control areas. In any case, London continues to regularly violate both NO_2 and fine particulate limits set by the World Health Organisation (WHO). A model for rather successful road-pricing is in Milan where road pricing has encouraged drivers to purchase cleaner vehicles resulting in a reduction of

PM_{10} levels (Gibson & Carnovale, 2015).

Examples of command-and-control policies designed to reduce pollution are traffic control, driving restrictions, plant closure, etc... A prime example is China's imposition of traffic control and plant closures to cut back on pollution and thus to improve air quality in Beijing during the Olympic Games. Chen et al. (2013) found that these actions decreased air pollution by approximately 25% compared to one year before the start of the games. Although the reductions were large and arguably health-enhancing, air quality improvements disappeared within one year after the Games had ended as these temporary measures were abandoned.

China has experimented with other policies. For example, Wang et al. (2014) assessed the effectiveness of national air pollution control policies and concluded that the National Total Emission Control (NTEC) had a positive impact on air quality improvement in China's metropolitan areas. Using panel data, Zheng et al. (2015) applied a fixed-effect model to study the effectiveness of the energy-saving and emission reduction regulations in 26 provinces and four municipalities during the period 2002-2011. Empirically, they found that these regulations have a positive impact on air quality.

Another common policy measure is driving restrictions. Davis (2008) examined their effectiveness in Mexico City. He compared the air quality prior to and after the implementation of the program using data from Mexico's monitoring stations on five main pollutants (SO_2, O_3, NO_2, CO, and NO_x). His analysis revealed that the policy had actually increased air pollution because drivers purchased additional (and often dirty) vehicles to avoid the driving restrictions. A similar finding was obtained by Zhang et al. (2017) for Bogota's driving restrictions.

Low emission zones are slightly less restrictive and usually only ban the worst polluters from entering city centers. Early evidence on their effectiveness in Germany was promising and showed that LEZs led to reductions of PM_{10} by about 9% (Wolff, 2014), although this estimate was later reduced to 4% (Gehrsitz, 2017) and the reductions appear to be too small to lead to tangible health improvements. In fact, the city of Frankfurt is currently considering a driving ban, not least because LEZs have failed to sufficiently reduce pollution levels, especially from Diesel-powered vehicles. LEZs have nonetheless been widely adopted in the European Union, Asia and in the United States, with limited success.

AQMAs are best thought of as "soft" command-and-control policies at the local level. They are, however, less restrictive in imposing counter-measures such as LEZs or let alone driving restrictions. At the same time, they lack market-based elements.

3 Data and Descriptive Statistics

The Department of Environment, Food and Rural Affairs (Defra) collects detailed data on local authorities' air quality and keeps track of declared AQMAs. Defra also provides advice on local air quality management including a range of support tools. Information on the latest pollution levels is collected by Defra's UK Air Information Resource (UK-AIR). They track concentrations of several pollutants, maintain a list of declared and revoked AQMAs, and detail the environment type of the various monitoring networks. In addition, Defra provides pollution forecast information and a data archive[2].

From Defra data, I constructed two main variables for this study: pollution levels - specifically the daily average NO_2 measurement for all major local authorities in the UK for the time period 1997 to 2016; and a list of local authorities that have declared an air quality management area (AQMA) within their territory. I obtained daily average NO_2 measurement from different monitoring stations that are distributed across several local authorities in the

[2]Local Air Quality Management guidance can be found on this website: http://laqm.defra.gov.uk/. UK Air Information Resource can be found on this website: http://uk-air.defra.gov.uk/.

UK. The majority of the local authorities have monitoring stations within their territory. **Figure** 4 shows the distribution of monitoring stations across the UK. Monitoring stations typically measure the level of NO_2 which is why the focus of this study is on this pollutant. Often information on NO_2, SO_2, PM_{10} & $PM_{2.5}$, O_3 and/or CO in the atmosphere is also collected. Notice that AQMAs have not been declared for pollutants such as Lead, Benzene or carbon dioxide (CO_2), although some stations monitor such pollutants.

Traffic and non-traffic background stations account for 90% of the monitoring stations all over the UK. 52% of these monitoring stations are background stations sited in residential areas, 38% are traffic stations located beside main streets and highways, while the rest of the monitoring stations are industrial stations. Traffic stations tend to be located in areas where air pollution levels are high. Indeed, it is expected that areas surrounding traffic stations are disproportionately affected by air quality policies because traffic stations monitor higher levels of air pollution compared to other stations types. Some of the monitoring stations have no available data for the period of interest and are, therefore, dropped from the sample. Out of 265 stations in the UK, only 212 stations are used in this study.

I have also collected weather data because temperature, rainfall, humidity, wind speed, and wind direction might affect air quality measurements. For example, Wang et al. (2010) used data of air pollution from stations near the Olympic Stadium in China to show that weather conditions could influence air quality and pollution levels. They show that part of the reduction in air pollution experienced during the 2008 Olympics Games was due to changes in rainfall, low temperature, and air mass from clean regions in China. However, detailed daily data on many weather covariates is not consistently and widely collected in the UK, especially for the late 1990s and 2000s. The only variables that are available at a regional level are monthly mean temperature and monthly rainfall. These data are collected by the "Met Office". I have therefore taken the analysis to the monthly level. That is I calculated monthly NO_2 averages for each local authority and matched in monthly temperature and precipitation measures from the closest weather station.

In addition to weather control variables, I also collected information on the type of each monitoring station, i.e. I have generated dummy variables equal to one for traffic, background rural, background urban, background suburban, industrial urban or industrial suburban stations, and equal to zero otherwise. I also gathered information on the economic characteristics of each local authority. In particular, the Office for National Statistics (ONS) provides annual measures of population size and unemployment rates for each local authority from 1996 to 2017. Values for both economic indicators are shown in the descriptive statistics, but – because they are only available annually – do not enter the regression analysis.

Table 1 divides the 125 local authorities with valid pollution measurements into three groups: "early-adopters" which first introduced an AQMA by the end of 2007; "late-adopters" which first introduced an AQMA after 2007 but before the end of the sample period; and "never-adopters" which never introduced an AQMA. The table then shows the annual means of the outcomes, the weather controls, and economic characteristics. In order to gauge the size of any immediate effect of an AQMA, I show the means for the 2 years prior to the introduction of an AQMA in a local authority as well as 2 years after such an introduction. For never-adopters, I show the means for 2007 and 2017.

Three things stand out. A first indication of **Table** 1 is that the declaration on an AQMA has little effect on NO_2 levels. In fact, raw NO_2 concentrations are slightly higher two years after an AQMA introduction for early-adopting local authorities. For late-adopting local authorities, average NO_2 levels are mostly constant at 25.24 $\mu g/m^3$ 2 years prior to the introduction of an AQMA and 25.72 $\mu g/m^3$ two years later. Second, we see that pollution levels were much lower in local authorities that have never declared an AQMA. Differences in levels are not a threat to my identification strategy to the extent that they are captured by local authority or station-fixed effects. Nonetheless, the fact that air quality is so much higher in the non-adopting community might limit the suitability of these local authorities as controls and motivates why I also run all specifications excluding stations from these areas. Finally, the table of means shows that early-, late, and never-adopting local authorities are reasonably similar to one another in terms of average rainfall, temperature, population size, and unemployment rate.

4 Empirical Framework

While the descriptive statistics suggest that AQMAs did little in the way of improving air quality, it may well be that the raw means are masking an effect that only becomes apparent when a more sophisticated regression method is deployed. The institutional features of AQMAs lend themselves to a difference-in-differences ("diff-in-diff") analysis that exploits the staggered introduction of the policy. The first-ever AQMA was declared in 1999 in London Borough of Westminster. Other local authorities - based on their review and assessment results of air quality - have declared the policy at different time periods. For example, Cardiff declared its first AQMA in December 2000, Belfast in July 2004, Mid Sussex in March 2012, and Merthyr Tydfil in January 2017 (Department of Environment Food and Rural Affairs, 2018). Intuitively, a diff-in-diff design deploys a rolling set of control local authorities that treatment local authorities are compared to, that is treatment local authorities are compared to control local authorities in periods where control local authorities have not themselves become treatment local authorities. The main identifying assumption is that after accounting for local authority specific time-invariant influences and after accounting for national trends, treatment and control local authorities would have followed similar air quality trends had treatment local authorities not declared AQMAs. Section **5** will present raw data and an event-study specification that support this assumption. The regression setting can also easily incorporate the fact that some local authorities revoked their AQMAs which they are allowed to do when air quality has either improved or other measures have been taken. I also experiment with including never-adopting local authorities which add more power to my analysis but may not be as comparable. As we will see, including these additional controls makes little difference. **Figure** 5 (5a & 5b) shows two maps of the 125 UK local authorities in the sample. Local authorities that have at any point in time declared an AQMA are highlighted in green. Out of 125, 100 local authorities had active AQMAs starting from 1999, but this process happened slowly over time. In 2000, only 10 local authorities had declared an AQMA. Over time, more and more local authorities became engaged in this air quality policy. By the end of 2007, 74 local authorities had declared AQMAs. Figure 5b shows that by the end of 2017, an additional 26 local authorities had active AQMAs. Note that, some local authorities have more than one AQMA within their territory. As of 2017, more than 700 areas have been declared air quality management areas. Of these, more than 90% are linked to emissions caused by traffic such as NO_2, SO_2, PM_{10} and $PM_{2.5}$.

A difference-in-differences approach is operationalized by running regressions that correspond to the following regression equation which is estimated using OLS:

$$y_{ijt} = \alpha + \beta Active_{jt} + \lambda X_{ijt} + \sum_{j=1}^{212} \theta_i Station_i + \sum_{t=1}^{240} \delta_t time_t + \epsilon_{ijt} \tag{1}$$

Where, y_{ijt} in Eq.1 is a vector for the outcomes of interest, namely the monthly average NO_2 level and the number of exceedance days in month “t” at monitoring station “i”, located in local authority “j”. β is the main coefficient of interest and the difference-in-differences estimate which indicates the causal effect of having an AQMA in operation on the outcome. $Active_{jt}$ is a dummy variable that is equal to one if local authority "j" has declared an AQMA at a certain point in time "t", and equal to zero otherwise. X_{ijt} is a matrix of control variables such as the monthly mean temperature, rainfall, and monitoring station characteristics. θ_i and δ_t are the monitoring station fixed effect and time fixed effect, respectively. The error term is represented by ϵ_{ijt}.

I estimated this regression using an unbalanced panel of 212 monitoring stations that are located in 125 local authorities over 20 years (240 months). I also deployed an event study specification to assess the dynamics (see more detail below) of an AQMA introduction, and experimented with station-specific linear time trends to assess the robustness of the main specification. As is best practice in diff-in-diff settings (Bertrand et al., 2004), I accounted for clustering at the local authority level. There are 125 clusters which should all but guarantee that the standard errors are asymptotically valid[3].

5 Results

5.1 Main Specification

Parallel trends in outcomes of treatment and control in the absence of the treatment is the key identifying assumption in this analysis. **Figure** 6 provides a first piece of evidence that this common time trends assumption might even hold when the potentially problematic sample of never-adopters is being used. The figure shows that the annual pollution level means across adopters and never-adopters move almost exactly in parallel. On the one hand, this supports the main identifying assumption. On the other hand, this again suggests that the introduction of AQMAs did little in the way of improving air quality as there is no break in the trend at any time even though more and more ever-adopting local authorities introduce AQMAs as time goes by.

This is confirmed by Panel A in **Table** 2 which displays the regression results of Eq.1 for all local authorities (ever-adopters and never-adopters), where the monthly average NO_2 is the outcome with monitoring station fixed effects and time (month) fixed effects included in all specification. In column (2) I add control variables for weather conditions and stations types. In column (3), I control for station-specific linear trends. All coefficients are positive but close to zero and either insignificant or borderline significant at the 5% level. The standard

[3]Sets of results where I cluster at the level of the monitoring station are available upon request. They yield virtually identical standard errors.

errors are precisely enough estimated to rule out any undetected negative effects. Taken at face value, an active AQMA is associated with an increase in monthly mean NO_2 levels of approximately by 0.8 μg/m^3. By way of comparison, the monthly average NO_2 concentration in the UK local authorities is 33μg/m^3, so this is a very small (and insignificant at the 1% level) effect of about a 2.5% increase in NO_2 levels.

The same regression is repeated separately for both background (non-traffic) monitoring stations - where the measurements for NO_2 levels would be expected to be lower as we move far away from streets congestion and traffics - and for traffic stations that are expected to be the most affected by air quality policies as they produce more emissions than other stations type. There is no indication of any statistically significant impact.

Panel B in **Table** 2 shows the results of the regression when only adopting local authorities are used. In other words, I discard the potentially inadequate observations from never-adopting units. The identifying variation here comes entirely from differential timing in the policy introduction. This specification is very much in the same ballpark as Panel A. An active AQMA is associated with an increase in the average monthly NO_2 level of 1.0 μg/m^3, or about 3%. The effect is statistically significant at the 5% level but not at the 1% level and statistically significant at the 10% level when I control for station-specific linear time trends. Again, the standard errors are small enough to rule out any substantial, undetected negative effects. Columns (4) to (9) focus on background and traffic stations for which I find very similar results.

The positive coefficients might be slightly surprising but are to some extent a mechanical feature of the AQMA declaration process. The active dummy captures both short-run and long-run effects of an AQMA. Bear in mind that AQMAs are only declared when a pollution threshold is crossed. Thus, by definition, the presence of an AQMA is initially likely associated with a small increase in pollution. The event-study specification in section 5.2 will confirm this positive short-run effect. What is surprising is that the overall effect remains positive. If

AQMAs were reducing pollution the β coefficient should overall be negative. The fact that this does not happen suggests that AQMAs indeed lack the teeth to push for improved air quality.

The effect of AQMAs on a measure of compliance with NO_2 daily pollution limits is documented in **Table** 3. The left-hand side variable here is the number of exceedance days on which the average NO_2 concentration of 40 $\mu g/m^3$ was exceeded. Panel A shows the impact of AQMAs on the number of exceedance days when all local authorities (ever-adopters and never-adopters) in the sample are used. The results indicate that there are no statistically significant effects in most of the specifications regardless of whether I consider all stations or just background and traffic stations respectively. However, columns (3) and (6) show that the coefficients are statistically significant at the 5% level when I control for station-specific linear time trends. Panel B repeats this exercise by limiting the sample to adopting local authorities. Columns (1) to (6) show statistically significant but very small coefficients. AQMAs increase the number of NO_2 exceedance days by approximately 0.5 days for all stations, 0.8 days for background stations, and reduce the number of exceedance days at traffic stations by 0.4. Again, I find no evidence of a negative relationship of the presence of an AQMA and improved air quality and the standard errors are precisely enough estimated to rule out any large undetected benefits.

5.2 Event Study Specification

The $Active_{jt}$ indicator in the main specification mixes short-run and long-run effects to give us an aggregate headline estimate of the effect of AQMAs. Not least because this effect is positive, it is worthwhile evaluating the dynamics of AQMA introductions. I do this by running an event-study specification in which the single $Active_{jt}$ indicator of Eq.1 is replaced with a set of 1-year leads and lags:

$$y_{ijt} = \alpha + \sum_{t=-3}^{t=4} \beta_t Active_{jt} + \lambda X_{ijt} + \sum_{j=1}^{212} \theta_i Station_i + \sum_{t=1}^{240} \delta_t time_t + \epsilon_{ijt} \tag{2}$$

The left-out reference period is the 3+ year lag and the final lag refers to time periods that are 4 or more years after the introduction of an AQMA. All other leads and lags follow 1-year increments. The first column of **Table** 4 presents the base specification augmented with the leads and lags for all local authorities. Two things stand out. First, all lags are statistically insignificant which strongly supports the common time-trends assumption underpinning the identification strategy. This also suggests that there is no evidence of an anticipatory response by local authorities about to declare an AQMA. Second, most of the positive association between AQMAs and pollution appears to occur in the long-run. In the periods around an AQMA's declaration, NO_2 levels increase only slightly. But most the main effect appears to be driven by pollution increases that occur years after the declaration of an AQMA. This strongly suggests that AQMAs fail to reign in air pollution in the long-run. The point estimate in column (1) suggests that in fact, long-run pollution levels are 1.4 μg/m^3 higher in the long run in local authorities with AQMAs relative to local authorities without AQMAs. This result is robust across specifications and the point estimate is even slightly larger when the sample is limited to ever-adopters (see columns (4) to (6)). **Figure** 7 plots the coefficients corresponding to the regression of Eq.2 along with 95% confidence intervals. For both **Figures** 7a and 7b, the intervals on the x-axis represent the number of years prior to or after the declaration of an AQMA. The figure illustrates very well that NO_2 levels in AQMA-declaring local authorities are mostly flat in the short-run but increase in the long-run.

Column (1) of **Table** 5 presents the results of the event-study specification for the number of monthly exceedance days. Again, most pre-treatment coefficients are statistically insignificant and hover around zero. There is no break in the trend around the adoption of an AQMA, again suggesting that the measure had no impact and the result is robust across specifications. **Figure** 8 illustrates this graphically.

5.3 Placebo Tests

As an additional robustness check, I have conducted a placebo intervention by changing the outcome as stated in Eq.3:

$$Rainfall_{ijt} = \alpha + \beta Active_{jt} + \lambda X_{ijt} + \sum_{j=1}^{212} \theta_i Station_i + \sum_{t=1}^{240} \delta_t time_t + \epsilon_{ijt} \tag{3}$$

Where $Rainfall_{ijt}$ is the monthly rainfall amount which is the depth of precipitation (mm) that occurs over a unit area (one meter squared) in month "t" at monitoring station "i", located in local authority "j". In other words, I replace the outcome of interest by a measure that cannot possibly be affected by the intervention of interest. Such a placebo test provides a useful falsification strategy to investigate whether the results might be driven by other unobservable factors that are time-invariant within a local authority and whose influence is not captured by the station-specific time trends. If I found an effect on my placebo outcome, this would cast doubt on my empirical design. **Table** 6 indicates that this is not the case. The effect of an active AQMA on rainfall in the placebo estimation is almost equal to zero and statistically insignificant at any reasonable level of significance, regardless of whether control variables are included or not.

6 Discussion and Conclusion

Air pollution is a major issue for many countries in the world from three interrelated dimensions: the environment, public health, and the economy. Governments have adopted stricter environmental polices and have undertaken serious national and local efforts to retain the environment and to protect public health as well as the economy. In 2017, the UK government announced a new plan to tackle roadside NO_2 concentrations as the policies that had been implemented were not as effective as it had been expected (Department of Environment Food and Rural Affairs, 2017). Local authorities have tried to tackle air pollution problems. Their ability to successfully reach air quality objectives and subsequently devise and implement air quality action plans (AQAPs), however, has been constrained by several factors. Most measures within an AQAP require close collaboration. Nevertheless, the lack of interdepartmental responsibility (Olowoporoku et al., 2010), the inconsistency between departmental policies that is reflected in local divergent agendas (Everard et al., 2013, Kilbane-Dawe, 2012), the absence of a strong local political will and the inability to raise awareness of local air quality (Carmichael & Lambert, 2011) affect the success of air quality measures taken by local governments. Indeed, air quality management, including monitoring and modelling, is an expensive process. Defra grants air quality funds, but they are limited and virtually always oversubscribed (Barnes et al., 2011). Consequently, a lack of funding may have put budget constraints on the local authorities' ability to implement more ambitious AQAPs.

Low air quality and its adverse effects prompted the UK government to announce its Air Quality Management Area (AQMA) policy in 1997. This decision delegated the responsibility to monitor air pollution to local authorities. As part of the policy, local policymakers were required to develop and implement measures to improve air quality when their measurements put them into violation Europe-wide pollution limits. Local authorities were allowed to design AQMAs as areas with increased investments into public transport, renewable energies or additional bike lanes, etc.. At first glance, giving responsibilities to the people on the ground rather than pursuing a national one-size-fits-all approach may have seemed appealing. However, this study shows that AQMAs have not been effective tools in reducing NO_2 concentrations which are primarily caused by vehicle emissions. My identification strategy exploits the fact that different local authorities introduced AQMAs at different points in time. This staggered introduction allows for the isolation of credibly causal effects using a difference-in-differences design. I find no significant reduction in NO_2 concentrations and obtain standard errors that are small enough to rule out any substantial pollution-reducing effects. In fact, this study provides evidence that air pollution continued to be on the rise years after the introduction of AQMAs.

AQMAs can be thought of as a "soft" command-and-control policy at the local level. The apparent failure of the policy to tackle air quality issues raises concerns about delegating such decision making on environmental policy to small local entities. However, there are some financial constraints that may limit the ability of local governments to adopt and to successful execute such policies. Local governments in the UK rely on three main sources to fund their services and expenditures, albeit in different proportions across services and time: property tax revenues, general grants from central government, and specific grants that target certain central government objectives. As part of its ongoing efforts to reduce public-sector deficits, the government implemented various austerity measures in 2010 and cut spending across all levels of government (Fetzer, 2019). Therefore, local governments have had to decide on which service areas to prioritise; for some service areas, the cuts have been greater [4]. In general, some of these services are relate to the action plans aimed at improving air quality at the local government level.

From a political economy point of view, this is hardly surprising. Failure to improve air quality is not sanctioned which limits local authorities' incentives to adopt robust measures that may hurt some constituents. This study on one of the UK's flagship environmental policies is thus best thought of as a cautionary tale on the effectiveness of local environmental policies without national government oversight, sanction mechanisms, or market-based approaches.

[4]For example, in England, the real-terms change in local government service spending for planning and development declined by over 55% (31.6% in Scotland and 52% in Wales), by over 10% for environmental services (8.1% in Scotland and 19.4% in Wales), and by 40% for transportation (22% in Scotland and 21% in Wales), from 2009-10 to 202016-17 (Smith et al., 2016).

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7 List of Tables and Figures

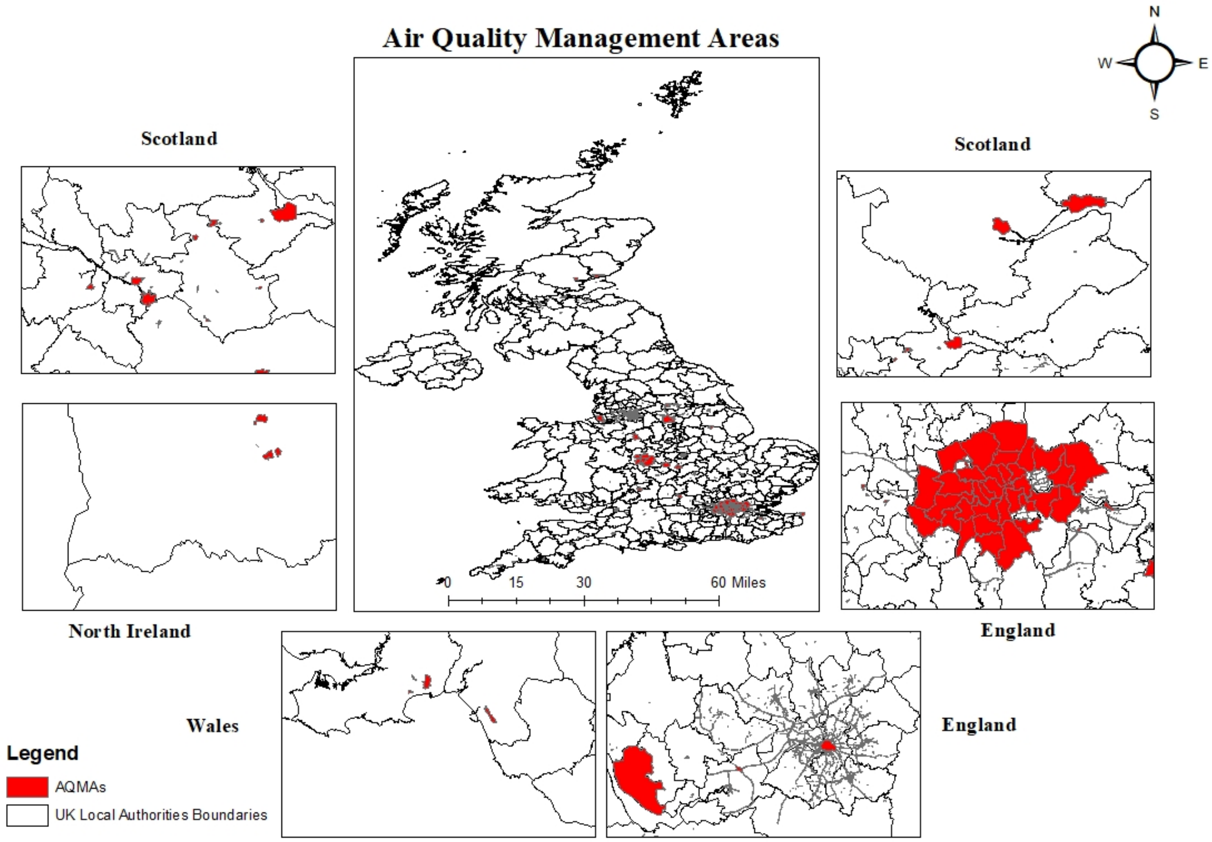


Figure 1: The Shape of Local Authorities' AQMAs.

Source: Map created by the authors from Defra's UK Air Information Resource (UK-AIR). Red areas are AQMAs.

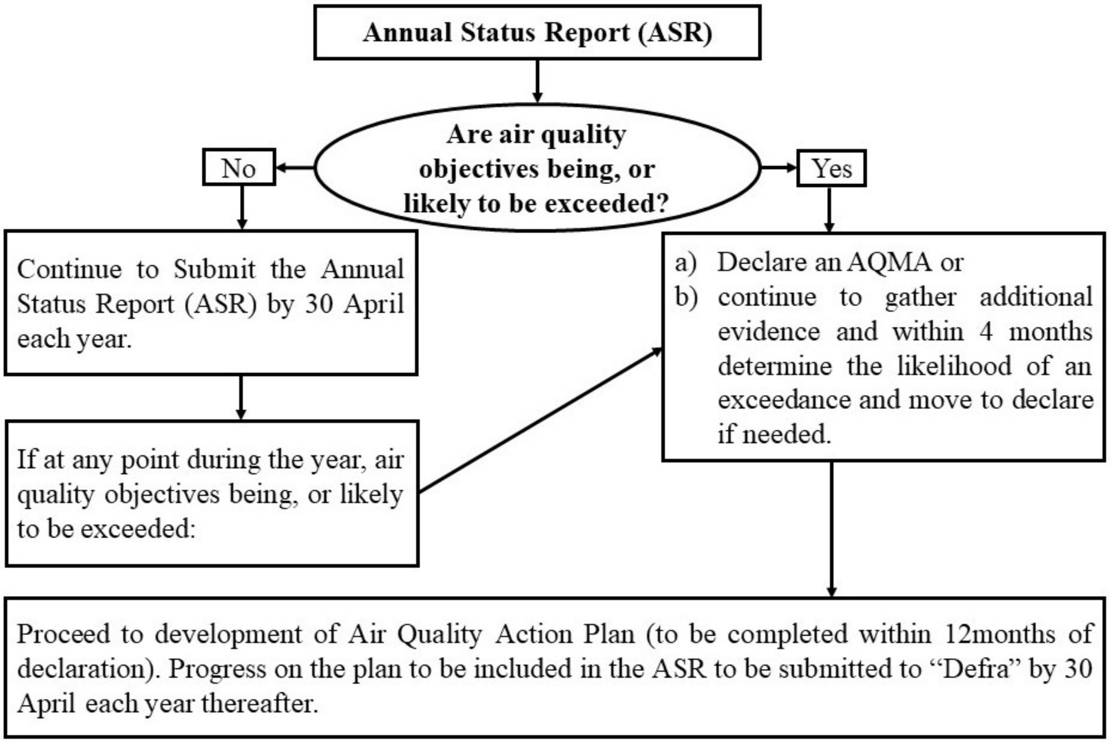


Figure 2: Overview of the process of AQMA's declaration (as of July 2015).

Source: Local Air Quality Management Policy Guidance (Department of Environment Food and Rural Affairs, 2016)

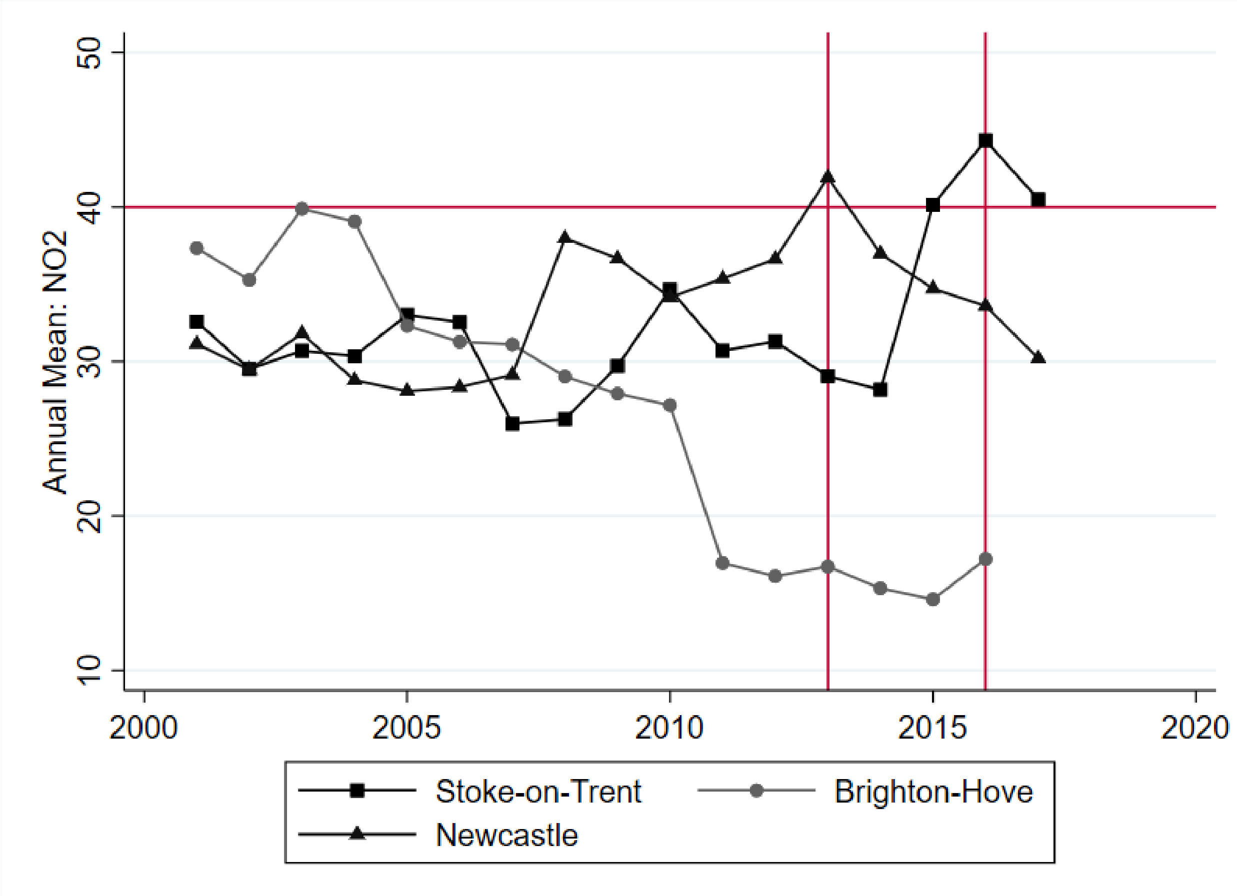


Figure 3: NO_2 Exceedance & AQMA's Declaration.

Source: Authors' calculations from Defra's UK Air Information Resource (UK-AIR).

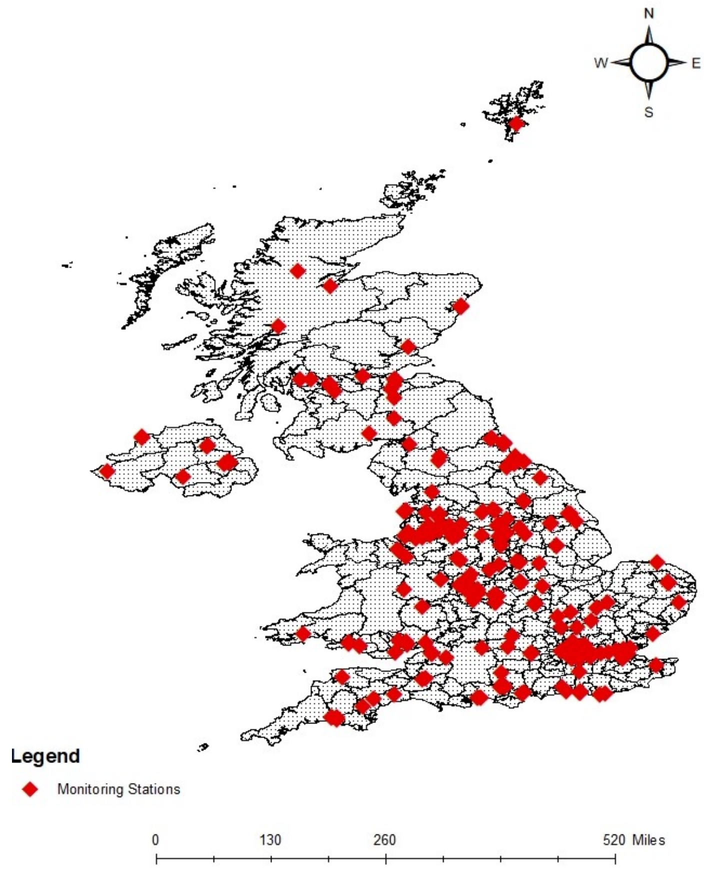


Figure 4: The Distribution of NO_2 Monitoring Stations Across the UK.

Source: Map created by the authors using Defra's UK Air Information Resource (UK-AIR).

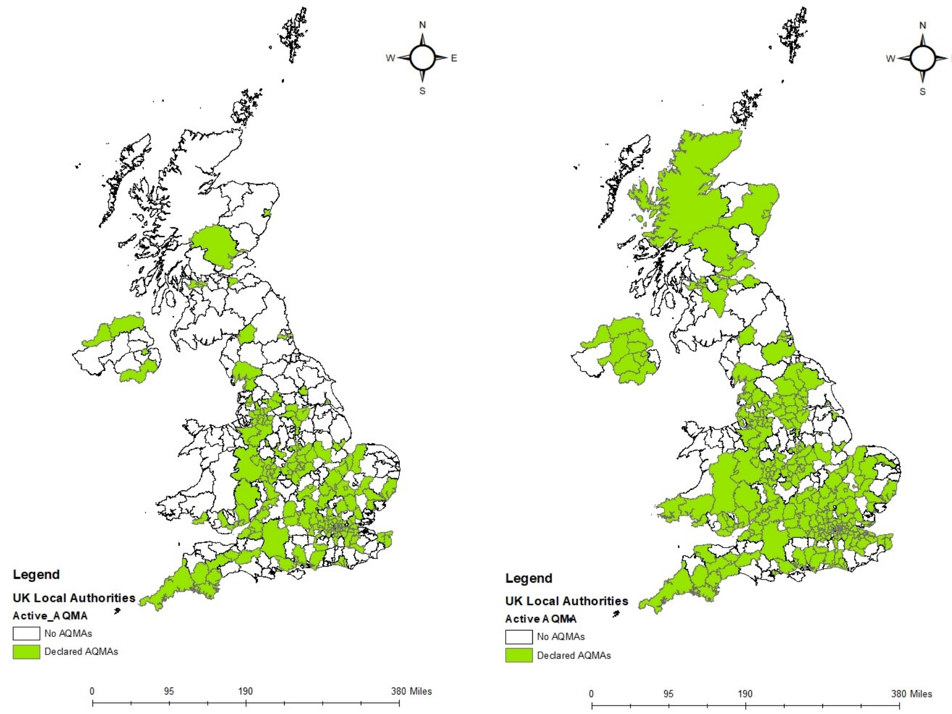
Table 1: Table of Means: Ever- vs. Never-adopters.

	Declared by the end of 2007		**Declared by the end of 2017**		**Never Declared**	
	2 years prior	2 years after	2 years prior	2 years after	by the end of 2007	by the end of 2017
Number of Local Authorities	74		26		25	
Outcomes						
Annual Average NO_2	36.25	37.82	25.24	24.72	21.78	17.57
# of exceedance Days	249.78	271.93	129.73	90.30	55.64	38.72
Weather controls						
Rainfall (in mm)	89.39	91.32	89.22	93.75	91.70	94.39
Temperature (in °C)	9.81	9.76	9.009	9.25	9.50	9.23

Local Authority Characteristics	**Declared by the end of 2007**	**Declared by the end of 2017**	**Never Declared**
Population	184401.93	161826.63	110436.23
Unemployment Rate (in %)	6.54	5.70	6.13
Geography			
% England	87.83	69.23	64
% North Ireland	2.7	7.69	0
% Scotland	4.07	15.38	20
% Wales	5.4	7.7	16

Notes: Average population size and average unemployment rates are taken annually from 1996 to 2017.

Data source: Defra's UK Air Information Resource (UK-AIR) for the outcomes. Met Office for the weather controls. UK Office for National Statistics for local authorities characteristics.



(a) Active AQMAs between 1999-2007 **(b)** Active AQMAs between 2008-2017

Figure 5: UK Local Authorities with Active AQMAs.

Source: Map created by the authors using Defra's UK Air Information Resource (UK-AIR). Green areas indicates the existance of an active AQMA/s in the local authority.

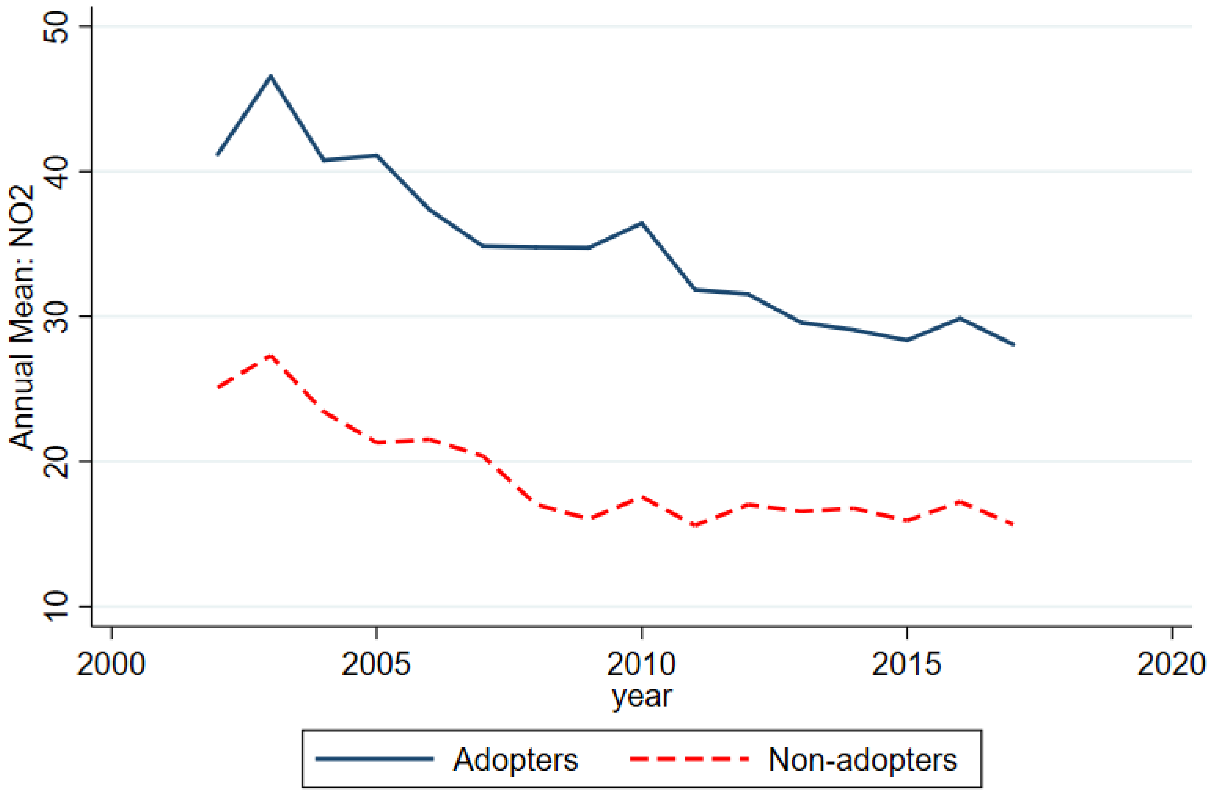


Figure 6: NO_2 Trend: Pre- & Post-Declaration.

Source: Authors' calculations from Defra's UK Air Information Resource (UK-AIR).

Table 2: Effect of AQMAs on air pollution: Diff-in-Diff estimates.

	All Stations			Background Stations			Traffic Stations		
Outcome: NO_2	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A (Ever- & Never-adopters)									
Active	0.835**	0.846**	0.826*	0.551	0.570	0.519	0.620	0.631	0.561
	(0.412)	(0.413)	(0.455)	(0.406)	(0.406)	(0.402)	(1.390)	(1.392)	(1.401)
Observations	24,026	24,026	24,026	15,650	15,650	15,650	6,535	6,535	6,535
R-squared	0.915	0.915	0.922	0.902	0.903	0.912	0.891	0.891	0.902
Panel B (Ever-adopters)									
Active	1.024**	1.039**	0.752*	0.954**	0.978**	0.459	0.923	0.957	0.373
	(0.422)	(0.422)	(0.452)	(0.435)	(0.432)	(0.411)	(1.537)	(1.536)	(1.508)
Observations	20,378	20,378	20,378	13,724	13,724	13,724	5,631	5,631	5,631
R-squared	0.909	0.909	0.917	0.893	0.892	0.903	0.882	0.882	0.894
Station Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Control Variables	-	✓	✓	-	✓	✓	-	✓	✓
Station-specific-trends	-	-	✓	-	-	✓	-	-	✓
SE Clustered at	LA	LA	LA	LA	LA	LA	LA	LA	LA

Robust standard errors (in parentheses) are clustered at the Local Authority (LA) Level. Regression results correspond to Eq.1. Dummy for Active AQMA is equal to one if at the time of NO_2 measurement, an AQMAs has been declared. Dependent variable is monthly mean NO_2 levels. Data Source: Defra's UK Air Information Resource (UK-AIR), daily pollution measurements (1997–2016).

*** Indicate significance at the 1% level.

** Indicate significance at the 5% level.

* Indicate significance at the 10% level.

Table 3: Effect of AQMAs on the number of Days with Exceedance: Diff-in-Diff estimates.

	All Stations			Background Stations			Traffic Stations		
Outcome: Exceedance Days	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A (Ever- & Never-adopters)									
Active	0.296	0.307	0.456**	0.310	0.323	0.590**	-0.329	-0.322	-0.392
	(0.212)	(0.213)	(0.222)	(0.268)	(0.270)	(0.254)	(0.494)	(0.488)	(0.454)
Observations	24,026	20,026	20,026	15,650	15,650	15,650	6,535	6,535	6,535
R-squared	0.822	0.822	0.834	0.779	0.779	0.795	0.809	0.809	0.82
Panel B (Ever-adopters)									
Active	0.563***	0.573***	0.440**	0.774***	0.795***	0.5857**	-0.376	-0.367	-0.443
	(0.200)	(0.200)	(0.221)	(0.24)	(0.241)	(0.255)	(0.520)	(0.510)	(0.461)
Observations	20,378	20,378	20,378	13,724	13,724	13,724	5,631	5,631	5,631
R-squared	0.819	0.818	0.830	0.779	0.779	0.794	0.796	0.796	0.808
Station Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Control Variables	-	✓	✓	-	✓	✓	-	✓	✓
Station-specific-trends	-	-	✓	-	-	✓	-	-	✓
SE Clustered at	LA	LA	LA	LA	LA	LA	LA	LA	LA

Robust standard errors (in parentheses) are clustered at the Local Authority (LA) Level. Regression results correspond to Eq.1. Dummy for Active AQMA is equal to one if at the time of NO_2 measurement, an AQMAs has been declared. Dependent variable is the number of days where NO_2 concentration of 40 μg/m^3 was exceeded on a given year. Data Source: Defra's UK Air Information Resource (UK-AIR), daily pollution measurements (1997–2016).

*** Indicate significance at the 1% level.

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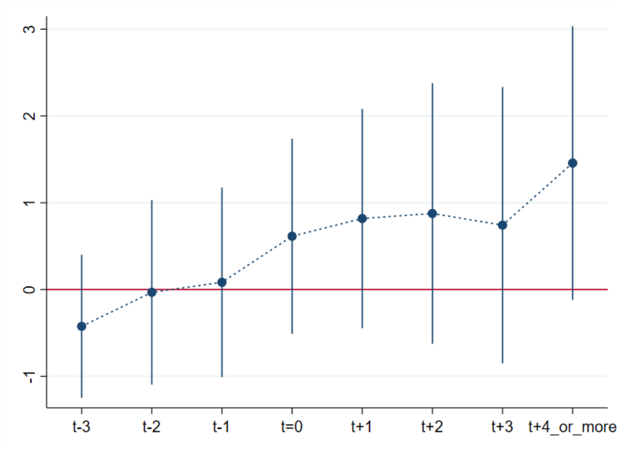
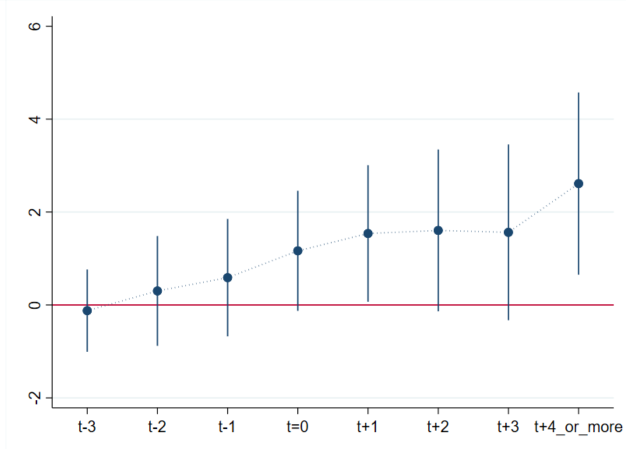
* Indicate significance at the 10% level.



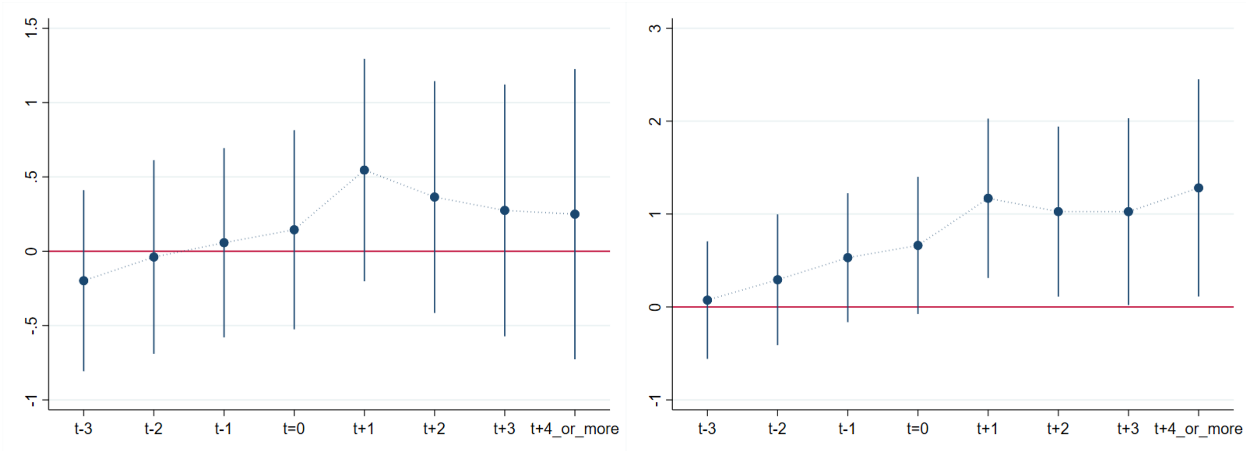
(a) Ever- & Never-adopters



(b) Ever-adopters

Figure 7: Event Study Regression Graphs: NO_2

Source: Authors' calculations from Defra's UK Air Information Resource (UK-AIR).



(a) Ever- & Never-adopters **(b)** Ever-adopters

Figure 8: Event Study Regression Graphs: Exceedance

Source: Authors' calculations from Defra's UK Air Information Resource (UK-AIR).

Table 4: Event Study Estimates: Ever- & Never-adopters

Outcome: NO_2	Ever- & Never-adopters (1)	(2)	(3)	Ever-adopters (4)	(5)	(6)
AQMA Declaration leads and lags						
Active_{t-3}	-0.424	-0.422	-0.083	-0.122	-0.120	-0.100
	(0.417)	(0.414)	(0.388)	(0.446)	(0.441)	(0.403)
Active_{t-2}	-0.032	-0.054	0.463	0.302	0.283	0.364
	(0.537)	(0.532)	(0.484)	(0.595)	(0.591)	(0.511)
Active_{t-1}	0.084	0.079	0.562	0.588	0.584	0.516
	(0.552)	(0.546)	(0.575)	(0.636)	(0.628)	(0.597)
Active_{t_0}	0.614	0.628	2.007**	1.165*	1.179*	1.950**
	(0.568)	(0.571)	(0.830)	(0.651)	(0.649)	(0.842)
Active_{t+1}	0.818	0.823	2.325**	1.538**	1.56**	2.325**
	(0.638)	(0.641)	(0.911)	(0.740)	(0.739)	(0.919)
Active_{t+2}	0.877	0.873	2.624**	1.605*	1.605*	2.523**
	(0.758)	(0.758)	(1.019)	(0.878)	(0.874)	(1.029)
Active_{t+3}	0.742	0.730	2.706**	1.563	1.556	2.597**
	(0.804)	(0.802)	(1.120)	(0.953)	(0.946)	(1.126)
$\text{Active}_{t+4ormore}$	1.458*	1.446*	4.053***	2.612***	2.603**	3.868***
	(0.796)	(0.792)	(1.435)	(0.988)	(0.980)	(1.408)
Observations	24,026	24,026	24,026	20,378	20,378	20,378
R-squared	0.915	0.915	0.915	0.909	0.909	0.917
Station Dummies	✓	✓	✓	✓	✓	✓
Month-Year Dummies	✓	✓	✓	✓	✓	✓
Covariates	-	✓	✓	-	✓	✓
Station-specific-trends	-	-	✓	-	-	✓
SE Clustered at	LA	LA	LA	LA	LA	LA

Robust standard errors (in parentheses) are clustered at the Local Authority (LA) Level. Regression results correspond to Eq.2. Dummy for Active AQMA - with leads and lags - is equal to one if at the time of NO_2 measurement, an AQMAs has been declared. Dependent variable is monthly NO_2 levels. Data Source: Defra's UK Air Information Resource (UK-AIR), daily pollution measurements (1997–2016).

*** Indicate significance at the 1% level.

** Indicate significance at the 5% level.

* Indicate significance at the 10% level.

Table 5: Event Study Estimates: Ever- & Never-adopters

	Ever- & Never-adopters			Ever-adopters		
Outcome: Exceedance	(1)	(2)	(3)	(4)	(5)	(6)
AQMA Declaration leads and lags						
Active_{t-3}	-0.198	-0.198	0.428	0.074	0.075	0.486
	(0.308)	(0.307)	(0.314)	(0.319)	(0.318)	(0.323)
Active_{t-2}	-0.039	-0.050	0.743**	0.293	0.280	0.785**
	(0.329)	(0.326)	(0.356)	(0.355)	(0.353)	(0.362)
Active_{t-1}	0.057	0.055	0.877**	0.531	0.526	0.973**
	(0.322)	(0.317)	(0.433)	(0.350)	(0.346)	(0.440)
Active_{t_0}	0.144	0.152	1.602***	0.663*	0.671*	1.681***
	(0.338)	(0.339)	(0.548)	(0.372)	(0.372)	(0.544)
Active_{t+1}	0.546	0.549	2.038***	1.170***	1.174***	2.152***
	(0.378)	(0.376)	(0.611)	(0.432)	(0.431)	(0.612)
Active_{t+2}	0.364	0.364	1.968***	1.027**	1.027**	2.050***
	(0.394)	(0.393)	(0.614)	(0.461)	(0.461)	(0.619)
Active_{t+3}	0.275	0.269	2.002***	1.026**	1.022**	2.104***
	(0.428)	(0.425)	(0.706)	(0.507)	(0.504)	(0.710)
$\text{Active}_{t+4ormore}$	0.249	0.244	2.214***	1.282**	1.276**	2.302***
	(0.493)	(0.490)	(0.762)	(0.589)	(0.588)	(0.764)
Observations	24,026	24,026	24,026	20,378	20,378	20,378
R-squared	0.915	0.915	0.922	0.909	0.909	0.917
Station Dummies	✓	✓	✓	✓	✓	✓
Month-Year Dummies	✓	✓	✓	✓	✓	✓
Covariates	-	✓	✓	-	✓	✓
Station-specific-trends	-	-	✓	-	-	✓
SE Clustered at	LA	LA	LA	LA	LA	LA

Robust standard errors (in parentheses) are clustered at the Local Authority (LA) Level. Regression results correspond to Eq.2. Dummy for Active AQMA - with leads and lags - is equal to one if at the time of NO_2 measurement, an AQMAs has been declared. Dependent variable is the number of days where NO_2 concentration of 40 $\mu g/m^3$ was exceeded on a given year. Data Source: Defra's UK Air Information Resource (UK-AIR), daily pollution measurements (1997–2016).

*** Indicate significance at the 1% level.

** Indicate significance at the 5% level.

* Indicate significance at the 10% level.

Table 6: Placebo Test: Rainfall

Placebo Outcome: Rainfall (Ever- & Never-adopters)	(1)	(2)
Active	0.508	0.588
	(0.605)	(0.586)
Observations	50,880	50,800
R-squared	0.792	0.794
Station Dummies	✓	✓
Month-Year Dummies	✓	✓
Control Variables	-	✓
SE Clustered at	LA	LA

Robust standard errors (in parentheses) are clustered at the Local Authority (LA) Level. Regression results correspond to Eq.3 with. Dummy for Active AQMA is equal to one if at the time of NO_2 measurement, an AQMAs has been declared. Dependent variable is the monthly amount of rainfall. Data Source: UK Met Office, monthly rainfall (1997–2016).