Examining the Spatial relationship between environmental health factors and house prices: NO2 problem?

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Abstract

Purpose: The impact of both air quality, noise and proximity to urban infrastructure can arguably have an important impact on the quality of life. Environmental quality (the price of good health) has become a central tenet for consumer choice in urban locales when deciding on a residential neighbourhood. Unlike the market for most tangible goods, the market for environmental quality does not yield an observable per unit price effect. As no explicit price exists for a unit of environmental quality, this paper utilizes the housing market to derive its implicit price and test whether these constituent elements of health and wellbeing are indeed capitalised into property prices and thus implicitly priced in the market place.

Design: A considerable number of studies have used hedonic pricing models incorporating spatial effects to assess the impact of air quality, noise and proximity to noise pollutants on property market pricing. This study presents a spatial analysis of air quality and noise pollution and their association with house prices, using 2,501 sale transactions for the period 2013. To assess the impact of the pollutants, three different spatial modelling approaches are employed, namely, an OLS using spatial dummies, a Geographically Weighted Regression and a Spatial Lag Model.

Findings: The findings suggest that air quality pollutants have an adverse impact on house prices which fluctuates across the urban area. The analysis suggests that the noise level does matter, although this varies significantly over the urban setting and varies by source.

Originality/value: Air quality and environmental noise pollution are important concerns for health and wellbeing. Noise impact seems to depend not only on the noise intensity to which dwellings are exposed but also on the nature of the noise source. This may suggest the presence of other externalities that arouse social aversion. This research presents an original study utilising advanced spatial modelling approaches. The research has value in further understanding the market impact of environmental factors and in providing findings to support local air zone management strategies, noise abatement and management strategies and is of value to the wider urban planning and public health disciplines.

KEY WORDS: housing markets, environmental health factors, air quality, noise pollution, house prices, GWR, SLM

Introduction

All locations experience an array of impacts from environmental factors, comprising both positive and negative dis(amenity) effects. However, some environmental factors, in addition to their potential to cause nuisance or loss of amenity, can have profound implications for the health and wellbeing of individuals living within affected areas. Existing research has tended to illustrate that prolonged exposure to poor air and noise quality comprises an adverse impact upon health in society in a number of ways, ranging from simple annoyance (Ouis, 2001; Ohrstrom *et al*., 2007; de Kluizenaar *et al*., 2013), sleep disturbance (Net, 2004), increasing risk of stroke[1] (Sørensen *et al.,* 2011), hypertension[1] (Jarup *et al*., 2008; Bodin *et al*., 2009), myocardial infarction (Babisch *et al*., 2005), and neuro-degenerative conditions (Rückerl et al., 2011; Chen et al., 2017). Indeed, in their recent study, Chen et al. (2017) found that residing adjacent to a congested road (within 50 metres) adversely affects cognition and the likelihood of higher incidence of dementia of up to 7%, with 11% of cases of dementia linked to air pollution.

It is trite that humans are adversely affected by expose to pollutants in ambient air. In response, the UK, in common with all EU member states, has an extensive environmental protection regime which has produced substantial improvements in environmental quality over the last seventy years. Urban areas for the most part, no longer suffer from sulphur dioxide and smog from coal burning which produced very visible pollution. Whilst various sources of visible air pollution have been largely remediated, by the implementation of clean air legislation and the uptake of the use of natural gas for home heating and energy generation, air pollution especially from road transport (nitrogen dioxide and particulate matter ($PM_{2.5}$)) and energy production continues to have major health and quality of life impacts, particularly exposure in urban settings. The increasingly problem of air quality has been highly publicised in popular media reports which showcase ongoing problems and challenges pertaining to both air and traffic pollution. Pertinently, across the UK, air pollution is estimated to contribute 40,000 deaths per annum. Indeed, recent reports have highlighted that combined the effects of long-term exposure to nitrogen dioxide (NO_2) and a particulate matter (PM2.5) in the UK's largest conurbation, London, is linked to 5,900 and 3,500 deaths respectively[2]. Indeed, a White paper issued by the London Assembly Health and Environment Committee (2012)[3] indicates that up to 9% of deaths in London are caused by air-borne man-made particles.

Under EU law, health based standards and objectives stipulate that the average hourly level of NO_2 in the air must not exceed 200 micrograms (per cubic metre) more than 18 times in a year[4]. Nonetheless, research has shown that EU-set limits on key pollutants have been frequently breached over the last decade and in large conurbations the stipulated EU annual air pollution limits have been breached in a matter of days[5] (London AQN, 2017)[6]. This has been witnessed on the legal front with the High Court ruling that existing approaches to tackle pollution are not sufficient and ordering urgent changes to regulate and 'clean' London's air. This has once again led to calls for sharper policy responses and solutions, with recommendations including the 'phasing out' of diesel vehicles, the creation of Ultra Low Emission Zones. The Government response has been to commit to channeling more funding resources into tackling air pollution in the UK of circa £875 million over the next five years[7].

In the UK, air quality is monitored by both central and local government with a regulatory system of air quality management and assessment setting air (environmental) quality standards and objectives for specific pollutants (DEFRA, 2007:13). The Air Quality Standards Regulations set out the responsibilities

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1 Traffic noise greater than 60dBA increases higher risk for stroke (Sørensen et al., 2011). Traffic noise [24-hour average] of 55 dBA @ a higher risk for hypertension (Bodin et al., 2009)

[2] http://www.bbc.co.uk/news/uk-england-london-33536989.

[3] London Assembly Health and Environment Committee (2012) Air Pollution in London, Issues Paper, December 2012.

[4] http://ec.europa.eu/environment/air/quality/standards.htm

[5] Annual air pollution limit breached on 19 occasions within a 5 day period for a south London road. At one point NO_2 levels were nearly double the legal limit. Putney High Street, which was the first London road to exceed its legal limit last year, went on to exceed the hourly limit more than 1,100 times in 2016.

[6] http://www.londonair.org.uk/LondonAir/General/research.aspx.

[7] https://tfl.gov.uk/info-for/media/press-releases/2017/june/mayor-launches-plan-to-improve-air-quality-on-the-tube

of local authorities in relation to air quality management and require that air quality reviews be conducted to assess the quality of air within local authority districts and that Air Quality Management Areas (AQMA) be declared where it appears that standards or objectives are not being achieved. In locations where the air quality objectives are not met, local authorities are required to produce an air quality action plan setting out how the standards will be met within a specified period. Yet despite these policy objectives and promises, in Northern Ireland, ambient air quality continues to pose detrimental effects on health and quality of life. The Department of Environment Farming and Rural Affairs (DEFRA, 2016) stated that recent evidence on the health impact of exposure to nitrogen dioxide has strengthened significantly, with reports persistently showing health warnings as a consequence of high levels of air pollution[8]. Indeed, evidence has been released directly linking Nitrogen Dioxide exposure to mortality rates. Additionally, in light of the fact that many of the sources of Nitrogen Dioxide are also sources of particulate matter (PM), the impact of exposure to particulate matter pollution (PM2.5) is estimated to have an effect on mortality equivalent to nearly 29,000 deaths (DEFRA, 2016:7). As a consequence, there are currently (as of 2017) 26 AQMA's declared in Northern Ireland; 19 of which are for Nitrogen Dioxide emissions from road traffic sources and the remainder principally for PM10 from domestic (solid fuel burning) sources. As a result, four Air Quality Managements Areas have been declared in the Belfast area in relation to Nitrogen Dioxide emissions from vehicles.

In a similar vein, whilst exposure to noise is inescapable and usually has limited impact on quality of life, in certain instances it can be so intrusive as to cause significant adverse effects on health (McKay and Murray, 2017). In a general sense, noise may be characterised as "environmental noise - noise from transportation and industrial sources; and neighbourhood noise - noise arising from within the community such as from entertainment premises, trade and business premises, construction noise and noise in the street (DoE NI, 2014:3). Nonetheless, noise is also a material planning consideration and "the planning system has a role to play in minimising the potential for adverse impact upon health and well-being through noise, by means of its influence on the location, layout and design of new development and consideration of the amenity impacts" (DoE NI, 2015:117). While nuisance legislation deals with noise from specific sources, the Environmental Noise Directive 2002/49/EC provides the framework to identify noise pollution levels and trigger the necessary action across the EU – generally implemented through the Environmental Noise Regulations within the UK. In Northern Ireland, the Environmental Noise Regulations 2006 (NI) which require a number of actions: namely the assessment of exposure to environmental noise; the provision of information on environmental noise and its effects on the public; preventing and reducing environmental noise and preserving environmental noise quality where it is good. These assessments have necessitated the production of strategic noise maps identifying areas which have roads with more than 3 million vehicle movements annually, railways with more than 30,000 train passages annually, airports with more than 50,000 movements annually and urban areas with more than 100,000 inhabitants.

Arguably, the exposure to air and noise pollution remains a major cause of ill health and mortality within the UK. Despite this acknowledgement, an important aspect of assessing the effectiveness of environmental policies that address the improvement of environmental air and noise quality is obtaining a quantitative measure of the economic value of any accrued benefits or negatives across geographic

[8] https://www.irishnews.com/news/northernirelandnews/2016/11/25/news/air-pollution-health-warnings-in-belfast-and-derry-801996/

neighbourhoods (Freeman 2003). In the absence of an explicit market for clean air (quality), and noise pollution, this paper empirically assesses whether these environmental amenities such as (perceived) good air quality and reduced noise levels are capitalised into property prices.

There are a variety of spatial based modelling frameworks in existence for examining house prices and housing markets. As discussed by Khalid (2015), a vast number of contemporary studies are incorporating explicit consideration of spatial effects in the estimation of hedonic price functions. This paper therefore examines three differing spatial methodologies to account for potential missing spatial variables, spatial trends and spatial heterogeneity when considering the effect of environmental concerns on house prices. We focus on three methods and consider some methodological issues associated with the estimation of an implicit price for clean air and noise by including a number of parameters and distance bands within the hedonic modelling frameworks. The rationale behind this approach is that, *ceteris paribus*, houses located in areas with cleaner air or reduced noise will have this benefit capitalized into their value - reflected in a higher or lower sales price. Interestingly, if environmental factors such as air and noise pollution, in addition to their recognised impacts on the health and wellbeing, also have an association with the price of residential property across a range of exposure levels (natural consequence) this perhaps illustrates a quadratic trade-off.

This is key for informing regional and local policy as to the (dis)amenity effect of noise and air quality, undoubtedly helping urban renewal and revitalisation strategies (intensification) and providing evidence base for the cost of 'good' or 'poor' planning. The paper proceeds as follows, Section 2 reviews the relevant literature related to house prices and the role of environmental quality – specifically air and noise attributes within housing markets. This is followed by the data and methodology section with results and a discussion presented in Section 4. Finally, conclusions are offered.

Literature

In the context of housing literature, amenities and environment effects are key considerations, and hedonic methods with spatial analyses have gained popularity to provide estimates of the proximity "effect" of a variety of positive and negative environment-specific externalities on property prices (McConnell and Walls, 2005). Numerous studies have examined proximate locational externalities (Kauko, 2003) demonstrating added or destroyed value based on the urban environment (Des Rosiers et al., 2002), neighbourhood style and distance and accessibility to amenities (Brunauer et al., 2013; Liao and Chen, 2013; Reed, 2013; Dube¨ et al., 2014) displaying mixed pricing effects. There is a long and evolutionary history investigating the relationship between air (quality) and noise (pollution) and property prices within hedonic price schedules, with the approach becoming an established methodology in environmental economics (Anselin and Lozano-Gracia, 2008).

Seminal studies examined the relationship between air pollution (dosages) and real estate values (Crocker, 1968; Reid, 1962; Ridker, 1967; Anderson and Crocker, 1971), illustrating the fundamental thesis that a portion of air pollution damage to artifacts and organisms is capitalised negatively into the value of land and immobile durable improvements thereon. The studies of Ridker and Henning (1967) and Harrison and Rubinfeld (1978) served to generate a voluminous literature base scrutinising the theoretical, methodological and empirical aspects of air quality (Anselin and Lozano-Gracia, 2008) suggesting that property value differences are a result of variations in air pollution. This is rife in numerous international based studies. In the Latin American context, a number of studies have examined the relationship between air quality and property value (Filippini and Martínez-Cruz, 2016). In Columbia, and primarily the

Bogotá region, Carriazo, Ready, and Shortle (2013) developed a hedonic price approach to estimate the value for an improvement in air quality based on rental property values. Employing a heteroskedastic frontier regression model to account for the bias[9], they found a consistent negative correlation between air quality and housing prices. Moreover, they established that the price elasticity for air quality was 25% higher in the OLS specification than in a frontier model with asymmetric random errors, implying that possible omitted variable bias in conventional hedonic models leads to the marginal value of air quality to be overestimated.

A Willingness to pay for air quality?

With regards to willingness to pay, in his seminal study, and on a more theoretic note, Nelson (1976) supports the existence of an implicit market for air quality – highlighting that the estimated price and income elasticities appear reasonable and suggest a means by which more exacting estimates of the benefits of air pollution abatement may be obtained, a finding also illustrated in the work of Harrison and Rubenfeld (1976) who revealed estimates for the willingness to pay for air quality improvements. In a similar vein, Smith and Huang (1995) conducted a Meta-analysis of MWTP for reducing particulate matter from hedonic property value models. Summarizing twenty-five years of property value/air pollution literature, Smith and Huang (1993, 1995) reported that approximately 74 percent of the studies found at least one significant air pollution variable, with many more recent studies primarily focusing upon the willingness-to-pay debate (Zabel & Kiel, 2000). To capture this effect has however proved challenging in terms of hedonic analysis as developing instruments to resolve endogeneity problems within hedonic analysis proving challenging. Early studies addressed the problem by pooling data from multiple spatial markets and using indicators for each area as instruments. One such study by Zabel and Kiel (2000) applying house price regressions for large U.S. cities (Chicago, Denver, Philadelphia, and Washington D.C.) found negative Marginal-Willingness-To-Pay (MWTP) for a one-unit increase in the concentration of particulate matter. In a similar vein, Chay and Greenstone (2005) exploit the quasi-random assignment of air pollution changes across counties induced by federally mandated air pollution regulations to identify the impact of particulate matter on property values. In order to solve the omitted variables problem, they use an instrumental variable approach in which they consider the Clean Air Act's (1970) nonattainment status designation for each county as the source of exogenous variability of pollution. Their findings reveal (cross-county) a high willingness to pay for clean air. According to their estimates, a variation of 1 g/m3 of particulate matter causes an increase of 0.20 percentage points in the average value of houses. Brasington and Hite (2005) in a more general paper relating environmental quality within a spatial framework, found a price elasticity of demand of –0.12, inferring environmental disamenities negatively affect the implicit prices of properties. Moreover, when considering nearby point-source pollutants they indicated that these depress house prices.

Further afield, the more recent study, Carriazo and Gomez-Mahecha (2018) evaluated whether there are welfare benefits related to air quality improvements in Bogotá using property values. Introducing a Second Stage hedonic model, they are able to identify a willingness-to-pay demand function to capture the non-marginal changes in air quality monetarily. Using Particulate Matter (PM_{10}), the authors use defined intra-urban housing sub-markets to identify an inverse demand function for PM_{10} reductions. The results confirmed that air quality is capitalized into property values which the authors conclude varies spatially across housing submarkets. Moreover, the results indicated that welfare estimates reveal that the monthly benefits of compliance with both the U.S. Environmental Protection Agency standard (50µg/m3 –annual average), and World Health Organization standard (20µg/m3 – annual average) command US$12.16 and US$189.64 per household, respectively. This the authors advocate highlights that intra-urban housing submarkets are suitable for the identification of a demand function to be used by policy

[9]unmeasured quality attributes of residential properties tend to be correlated with the environmental quality attribute of interest and asymmetrically distributed across properties

makers interested in evaluating non-marginal benefits (costs) from air quality improvements (deterioration). A comparable study by Zhang et al. (2017) valuing air quality in China, estimates the monetary value of cutting PM2.5. Matching hedonic happiness in a nationally representative survey with daily air quality data the authors estimate, that on average, a willingness to pay premium of ¥258 ($42, or 1.8% of annual household per capita income) per year per person for a 1% reduction in PM2.5. A further study in China conducted by Chen, Hao and Yoon (2018), measured the welfare cost of air pollution in Shanghai. Implementing a hedonic method using housing price and air quality data, the results showed air pollution has a significant and negative impact on housing price and that the willingness to pay for better air quality varies significantly across different income groups.

Spatial modelling of Air Quality

In terms of modelling approaches, research has verified, modified, and redefined the economic interpretation of the MWTP relationship (Beron et al., 2001). In the context of the valuation of environmental amenities, the recent literature, whilst less common to other papers investigating externality issues, has introduced more spatially based models in an attempt to capture the relationship between air quality and house prices. Generally, these studies have more typically adopted a theoretic stance scrutinising potential bias and loss of efficiency that can result when spatial effects such as spatial autocorrelation and spatial heterogeneity are not accounted for. In this regard, a theoretical perspective is offered in Small and Steimetz (2006) using data for housing rents. Investigating the implications of spatial autoregression for measuring the marginal welfare effects due to a change in a residential amenity such as air quality, they illustrate that a spatial-autoregression has superiority for determining implicit prices when spatial spill-overs are present.

Equally, Anselin and Lozano-Gracia (2008) examined the valuation of ambient air quality in spatial hedonic models and discussed the theoretical issues for estimation, namely the endogeneity in the form of errors in variables for the interpolated measures of air pollution. Employing a spatial two stage least squares estimation with instruments for the spatially lagged dependent variable, as well as inclusion of the coordinates of house locations and their interaction as instruments for the interpolated pollution values, they highlighted the importance of correcting for variable errors in interpolated pollution values. Pertinently, the authors advocated that employing a spatial lag specification allows for a distinction between direct effects and the role of a spatial multiplier, which are combined in the estimates of the non-spatial models. They strongly encourage that accounting for errors in variables of the interpolated pollution measures need to become a mandatory element of applied work in spatial hedonic models when considering ambient air quality.

Other recent applications include Kim et al. (2003) who set about to improve the methodology for estimating hedonic price functions when considering ‘inherently spatial' data. The authors developed a spatial-econometric hedonic housing price model for the Seoul metropolitan area to measure the marginal value of improvements in sulphur dioxide (SO_2) and nitrogen dioxide (NO_x) concentrations. Their diagnostic findings revealed the spatial-lag model to be superlative – exhibiting that SO_2 pollution levels have a significant impact on housing prices, with NO_x showing no statistically significant impact. Anselin and Le Gallo (2006) using a sample of 115,732 house prices investigated the sensitivity of hedonic models of house prices to the spatial interpolation of measures of air quality. Comparing Thiessen polygons, inverse distance weighting, Kriging and splines to conduct spatial interpolation of point measures, they employed both maximum-likelihood and general method of moments techniques in the estimation of the hedonic. Their findings showed a high degree of residual spatial autocorrelation present necessitating the inclusion of a spatially lagged dependent variable. A noteworthy finding in their study was the evidence of 'significant' differences across interpolators in the coefficients of ozone, as well as in the estimates of willingness to pay. Moreover, their results showcased the Kriging technique to provide the best results in terms of estimates (signs), model fit and interpretation. Pertinently, they claim that using a categorical measure for ozone is superior to a continuous measure.

Finally Zheng *et al*. (2009) conducted research into the relationship between house prices, investment flows (FDI) and ambient air pollution across a suite of major Chinese cities. Their findings revealed "green amenities" to be capitalized into cross-city housing prices. More specifically, their results showed house prices are lower in cities with higher ambient pollution levels, and that this marginal valuation for green amenities is rising over time. In addition, they suggested that cities experiencing (higher) inflows of FDI have lower air pollution levels than observationally identical cities, which raises questions towards sustainable development policy and health.

Noise pollution

Several house price studies have assessed the impact of noise on property values using both hedonic and spatial modelling approaches[10] depicting reduced welfare as a result of heightened noise and the reduced property value. With regards to traffic noise pollution, there is an extensive evidence base pertaining to the European experience, primarily due to extensive, readily available data from public bodies and government sources. In the UK, Day *et al*. (2007) and Blanco and Flindell (2011), undertook two very dissimilar studies to quantify traffic noise 'value'. Day et al. (2007) conducted a revealed preference study into the different effects of road traffic noise on property values. Meanwhile, Blanco and Flindell (2011) using a two-stage hedonic pricing approach illustrated that a semiparametric spatial smoothing estimator outperforms other standard specifications. Likewise, Nellthrop et al. (2007) in a WTP perspective examined transport□related noise for an appraisal based analysis using the city of Birmingham in the UK. They found that WTP estimates are comparable with their European counterparts and that there is a case for a lower threshold at 45 dB(A)Leq,18h rather than the more conventional 55 dB(A) for 'background' noise thresholds.

In the Swedish context, Wilhelmsson (2000) conducted research examining the Impact of Traffic Noise. Their empirical analysis using a spatial lag model and a spatial autoregressive error model to account for spatial autocorrelation in the residuals revealed an average noise discount of 0.6% of the house price per decibel or a total discount of 30% of the price for a house in a noisy location compared with a house in a quiet one. Similarly, Andersson et al. (2010) explored the relationship between property prices and the exposure to multiple noise sources, namely road and railway noise. The study used a hedonic approach, finding road noise to comprise a larger negative impact on the property prices than railway noise. Baranzini *et al*. (2010) differentiated between the use of measured and perceived noise in a hedonic price model for Switzerland to analyse whether property prices are affected by environmental characteristics. Employing data containing both objective and perceived noise, they found that the coefficients, including those on noise, are statistically equal across models confirming a convergence in the perceived and measured noise variables. In the Spanish context, Duarte and Tamez (2009) ran an OLS, GWR, and SLM approach controlling for structural characteristics, neighbourhood and accessibility, concluding that noise does matter for the spatial formation of real estate values. Their findings also signified the

[10] For a full review see Bateman *et al.*, 2001; Navrud, 2002; Bjørner, 2003; Nelson, 2008.

GWR model to be superior suggesting that there are spatial dependencies (resolved by the autoregressive model), but also spatial heterogeneity. In the Dutch market, Theebe (2004) examined the impact of traffic noise on prices, finding that each additional unit change in dB level reduces property price by 0.4%. Interestingly, their results provided evidence (albeit weak) that proprieties in high-income areas are affected more by traffic noise more than those in low-income areas. Brandt and Maennig (2011) also illustrated price discounts in the amount of 0.23% following a 1 dB(A) increase in road noise for condominium prices in Hamburg, Germany.

In the USA, research has tended to apply more indirect measures of traffic noise. Chernobai *et al.* (2009) analysed non-linearities in both the effect of distance from the highway and the effect of time relative to the completion of the road segment - the effect of a newly completed highway extension on home prices in the surrounding area. Using home sales data over an 11 year period they combined a standard hedonic model incorporating splines to allow for non-linear variations of the effect along the temporal and spatial dimensions. The results showed a proximal effect of the pricing as a consequence of distance. In their study, Li and Saphores (2012), explored the impact of freeway traffic (and truck traffic specifically) on 4,715 single-family houses using a fine-grained fixed effects model. They revealed that a 1% increase in total traffic reduced price by merely $24 (located within 100 m of a freeway). By contrast, a 1% increase in truck traffic would decrease the value of a $420,000 house located between 100 and 400 m from the nearest freeway by $2,000 to $2,750. More recently, Seo et al. (2014) analysed the positive and negative relationships between housing prices and proximity to light rail and highways in Phoenix, Arizona. Their results showed that proximity to transport nodes was associated significantly and positively with single-family detached home values. Interestingly, factoring in distance, the proximity of distance from highway and LRT stations form an inverted-U (quadratic) pattern consistent with a positive longer-range distance–decay accessibility effect, minus a smaller and shorter-range distance–decay disamenity effect. Swoboda et al. (2015) in their traffic noise study, estimated a hedonic price function for single-family houses using LWR techniques for the St. Paul, Minnesota, urban area. Specifically, they estimated semi-logarithmic regressions, both geographically and temporally, finding no evidence of spatial non-stationarity of the noise coefficient.

Overall, there is a wealth of literature, both historical and contemporary which examines the implications of environmental health parameters and proximity to pollution sources in relation to house prices. More recent studies have capitalised on the innovative developments within spatial econometrics – tending to examine the technical nature and aspects of the multifarious modelling methodologies which have emerged. Regardless of their specification, the literature has had a tendency to demonstrate a spatial association between house prices (negatively) and wider environment pollution (quality). This is important given that it reveals information about the willingness to pay for air quality — a nonmarket commodity. Moreover, to the extent that policymakers use the results from air pollution/property value studies, the findings are socially relevant.

Methodology

Data

House price data is drawn from the University of Ulster House Price Index from the period covering 2013 for the Belfast Housing Market. This period was selected as it is concurrent with the publication of both the Air Quality Background Concentration Map database and noise estimate database. In total, 2,501 transactions are used in the study after variable cleansing and employing Mahalanobis distance criteria for removing outliers and a data merge to obtain the *X, Y* coordinates. The air quality data was derived from the Department of Agriculture, Environment and Rural Affairs (DAERA) Air Quality Background Concentration Map database[11]. The database provides point co-ordinates for estimates of concentrations of specific pollutants with the data at a resolution of one point per square kilometre. These point sources were merged with a square kilometre (Km^2) grid layer for Northern Ireland to provide area cover for the Belfast market (**Figure I**).

<<<Figure I House Prices and Air pollution variables>>>

The concentration of particular pollutants in the database is derived from local emission sources such as roads, airports, residential and industrial chimneys together with emissions dispersed by the wind. The data for air quality particulate matter ($PM_{2.5}\mu g/m^3$) and Nitrogen dioxide (NO_2 $\mu g/m^3$) provide concentration levels over various time intervals (ranging from 15 minute real-time updates, 24 hour running averages to weekly, monthly and annual averages)[12]. The data used in this study is expressed as total Mean Concentrations per square kilometre (Table I).

<<< Table I Air Quality Variable Descriptions>>>

Noise data was also obtained from the government department (DAERA), developed in 2012 under the requirements of the Environmental Noise Directive[13]. The mapped data estimates noise levels from sources such as major arterial roads, railways, airports and urban agglomerations (Figure II). The noise measurements selected for the analysis in this research are the Equivalent Continuous Sound Level (Leq)[14]. Given that most community and industrial noise measurements are A-weighted,[15] LAeq is employed within the confines of the study where the sound level in decibels equivalent to the total A-weighted sound energy level measured over a 12-hour period from 07.00 - 19.00 hours. This represents the travel to work times and patterns reflecting average daytime noise exposure levels experienced at particular locations. Pertinently, the dB for noise ranges are used instead of the noise index as this allows for the (exponential) nonlinear relationships between noise levels and property pricing to be assessed[16].

<<< Figure II Noise pollution variables>>>

The spatial analysis was undertaken by layering databases of environmental pollutants, infrastructure and house price data using Geographical Information Software (GIS). In addition to the data on noise and specific pollutants additional data was also incorporated into the GIS mapping to account for proximity to pollutants sources, including the location of major roads and airport runways. The NO_2 data ranged in value from 7.40 – 29.66 $\mu g/m^3$. This was categorised and brought into the model as a fixed effect using

[11] This Area air quality particle concentration map uses 2013 as the reference year.

[12] *See:http://www.airqualityni.co.uk/?site_id=BEL0&view=graphing*http://www.airqualityni.co.uk/data/download-data?ds%5Bp%5D%5Bsqid%5D=45602#statistic-type

[13] In accordance with EU Statute.

[14] The official IEC Definition of Leq: Equivalent Continuous Sound Level Definition IEC 801-22-16, logarithm of the ratio of a given time-mean-square, standard-frequency-weighted sound pressure for a stated time period, to the square of the reference sound pressure of 20 μPa

[15] The A-weighting filter covers the full audio range - 20 Hz to 20 kHz and the shape is similar to the response of the human ear at the lower levels. A-weighted measurements correlate well with the perceived loudness at low sound levels.

[16] Similar to Nellthrop et al. (2007); Theebe (2004) dB (banded) who account for non-linearity and fixed effects

discreet bands (e.g. low, moderate, high and very high) to ensure robust sampling and permit meaningful analysis (Table II). This was also the case for the $PM_{2.5}$ data which ranged from 8.06 - 13.87 μg/m^3.

Distance buffer intervals were further created around these infrastructure (pollutant) sources (25 metre or 100 metre bands) to provide distance contours to the specific type of infrastructure. Incorporation of these distance buffers afford locational context to the pollutant background concentrations (Table III).

<<< Table III Distance variables frequency sampling>>>

The house price data was added as a layer and spatial joins undertaken to merge the pollutants, noise, infrastructure buffers into a single (spatially referenced) database. All variables, where appropriate, were transformed into binary state. AQMAs[17] were accounted for using a binary variable 1 if within the air quality management zone; 0 otherwise, to categorises all properties within the designated zone and furthermore those proximal (within 300 metres). An additional element which surfaced from the literature pertained to the 'flight path' effect. This was also incorporated into the OLS and GWR models to investigate whether properties currently under the existing flight path are impacted upon by aircraft noise. The data was subsequently exported into the statistical packages EViews and *R* to permit geo-statistical analysis. A description of the data variables employed within the study is evidenced in Table IV below.

<<< Table IV Variable Descriptions>>>

Modelling approaches

The need for spatial consideration within hedonic pricing models has long been a concern within the valuation arena as both supply and demand of real estate will vary across a given location as tastes, preferences, willingness, and abilities to buy flucutate. Early studies by Ball (1973) and Berry and Bedarz (1975) presented arguments for the importance of including spatial variables in valuation and house price models – concluding that a traditional ordinary least squares (OLS) model that treats all locations equally is flawed; error terms will likely fluctuate across submarkets, and will also be correlated with similar, nearby properties, therefore violating the assumption of a constant error variance (in residuals) which may occur due to structural instability of parameters across space, modelled functional forms that are not spatially representative, or missing variables (Anselin, 1988). As identified by Khalid (2015) spatial effects within cross-sectional data can imply that at least one type of group-effect was overlooked which can result in market segmentation due to disequilibrium in demand and supply tastes (structures) thereby furnishing differences in shadow prices for a given market attribute (Thibodeau, 1998). This also gives rise to the absence of market disaggregation as a consequence of demand and supply interacting across geographic markets which results in arbitrage price differences in different locations (Palmquist, 1989).

The implementation of spatial dummy variables (e.g. neighbourhood indicator variables) and distance-based variables (e.g. kilometres or minutes to city-centre) often improves OLS model performance by helping to account, at least in part, for spatial (dis)similarity. However, such variables are considered to not fully satisfy the assumption of constant error variance across observations, and ultimately leave coefficients biased (Fotheringham et al., 2002; McMillen 2010). As pointed out by Osland (2010), spatial patterns in parameters may be assumed to exist continuously or discontinuously with a fundamental

[17]The Environment (Northern Ireland) Order 2002 states local air quality management process and the procedures that district councils should follow when carrying out their duties. Art 11 of the Order provides that every district council shall review the air quality within its area at the present time and assess the likely future quality.

criticism against applying a discontinuous demarcation of the geography is that the study area is sometimes arbitrarily delineated.

This corresponds to two fundamental concepts and concerns when employing spatial models, namely the heteroscedastic errors present in a model, and the pattern of interaction termed the adjacency effect (Can, 1992). In this regard, spatial effects can be considered a result of spatial non-stationarity or dependance (autocorrelation) and spatial heterogeneity (Anselin, 1988; Dubin, 1992; Osland, 2010). Indeed, Can (1990:256) provides the following explanation of the two characteristics: ''Spatial dependence refers to the possible occurrence of interdependence among observations that are viewed in geographic space, and violates the assumption of uncorrelated error terms … with Spatial heterogeneity referring to the systematic variation in the behaviour of a given process across space, and usually leads to heteroskedastic error terms''.

Given these statistical concerns, studies have tended to examine these theoretical challenges to better account for spatial dependence and heterogeneity. A plethora of spatial studies have incorporated an expansive array of spatial effects to account for location in hedonic price modelling. According to Gao, Asami, and Chung (2006), these various approaches incorporate spatial structural instability; spatial drift and spatial lags to reduce error terms; and spatial independence. As a result, various pricing studies (Casetti, 1972; Can, 1992; Casetti, 1997; Thériaut, Des Rosiers, Villeneuve, & Kestens, 2003; Pace and LeSage, 2004; Brunstad et al.,1995; Huang et al., 2006; Kim et al., 2003; Patton and McErlean, 2003; Cotteleer et al., 2008 and Kuethe, 2012) have been able to exploit the spatial nature of residential data-sets to account for spatial causation within the regression framework. There have also been a number of alternative semi-parametric and non-parametric approaches introduced to specifically model spatial dependence, such as Kriging (Diggle & Ribeiro, 2007) and co-kriging techniques (Haas, 1996). Pertinently, the GWR approach has assumed greater prominence in recent years for price estimation, as it isolates and combines spatial dependency and heterogeneity, accounting for locational or adjacency effects and market segmentation (Pàez, 2005; McMillen, 1996).

Such spatial regression models typically achieve superior results than OLS models – both with and without spatial variables (Borst and McCluskey 2008; Fotheringham et al., 2002; McMillen 2010; Moore 2009; Lockwood and Rossini 2011; McCluskey et al. 2013; Bidanset and Lombard 2014), as by incorporating geographic information systems (GIS), spatially-adjusted model structures are able to include a distance-based weights matrix based on each observations *X,Y* coordinates (latitude and longitude) and test for correlations between observed data due to geographical proximity and similarity. Valente et al. (2005) states that this local variation explicitly addresses spatial dependency as a continuous function which permits the analysis of relationships between properties varying depending on distance from one another. Indeed, research undertaken by Bowen, Mikelbank, and Prestegaard (2001) discussed these theoretical issues regarding 'space' in the context of hedonic housing price studies, ultimately advocating for the use of spatial diagnostics in hedonic house price estimation. Similarly, Pace, Barry, and Sirmans (1998) show that using spatial econometrics is preferable to including a long list of proximity variables for different amenities, illustrating that the various approaches controlling for spatial dependence negates the necessity to do so.

In addition, from a spatial econometric theoretical perspective, neglecting the inclusion of a spatially lagged dependent variable (spatial autocorrelation) can lead to biased parameter estimates as a result of spatial dependence which can be defined as the interdependence among house prices due to their relative geographic locations from each other (see Fulcher, 2004; Bell and Bockstael, 2000). Thus, if it is suspected that house prices are partly explained by prices of nearby and similar properties, then spatial dependence models are necessary to correct for this effect and other spatial attributes not captured by the model. Such indirect impacts are in addition to the direct effects associated with the standard explanatory variables that capture the structural features of the housing units, neighbourhood characteristics, and attributes of the social and natural environment (Kim et al., 2003). These induced effects arise because the price of houses depends on the prices of the neighbours[18].

Model selection

Khalid (2015) emphasises that model selection is therefore extremely critical to unveil a 'final' model which best describes market realities and available data. This, as highlighted by Brown et al. (2001), has been the case for an extant number of studies which continue to employ traditional based hedonic approaches and introduce spatial features. Whilst there has been a concentration on geostatistical approaches, McCluskey et al. (2013) do point out that reviews on model comparisons show that each (respective) technique has its specific advantages and disadvantages. Kauko and D'Amato (2008) concur with this citing the lack of consensus for a single, dominant methodology. Indeed, as acknowledged by Brown et al. (2001), despite some inherent limitations of hedonic approaches in explaining the fluctuation of prices across time and space, research has however illustrated that these types of models are of use when presented against more spatially delineated models and in a number of instances demonstrate mixed results (Khalid, 2015) and equifinality across modelling outcomes (McCluskey et al., 2013). This equifinality debate is also acknowledged by Osland (2010) who suggests that despite the conceptual appeal of spatial analysis to researchers and research-users, its execution can be quite involved, whereas the results do not always lend themselves easily to policy-making applications. This is also highlighted by Muller and Loomis (2008) who also caution that the gap between coefficients corrected and uncorrected for spatial dependence may not always be economically significant – inferring that the inefficiency attributable to spatial influences may not be large enough to cause critical errors in policy decisions.

As identified by Osland (2010), given that the choice of spatial model will have an effect on the economic interpretation of the estimated coefficients, this paper employs three spatial models namely a traditional hedonic model (incorporating spatially delineated government districts), a GWR method and a SLM approach in order to test (and triangulate) the effect of the selected pollution parameters on house prices. The OLS (spatial regime) model is used to serve as a base model to analyse the impact of the air and noise pollution externalities. The GWR is used to tackle the issue of spatial heterogeneity and autocorrelation as this locally weighted least squares method is non-parametric, thus not requiring any assumptions to be made regarding the underlying distributions of values of the predictor variables, and therefore has the ability to handle highly skewed and categorical predictors (Moore & Myers, 2010). Finally, a number of studies have successfully adopted a spatial lag method, (Kim, Phipps, & Anselin, 2003; Shin, Washington, & Choi, 2007; Wilhelmsson, 2002). Following the approach adopted by Kim, Phipps and Anselin (2003) and of Bowen, Mikelbank, and Prestegaard (2001), we employ a spatial-lag model which implicitly assumes that the spatially weighted average of housing prices in a neighborhood affects the price of each house (indirect effects) in addition to the standard explanatory variables of housing and neighborhood characteristics (direct effects)[19]. This was further due to the restriction of the sample to a single year cross section and allows for a direct correspondence of our house sale price and characteristics data with the noise contour and air quality data[20]. As outlined by Brueckner (2003), the spatial-lag model is particularly appropriate when there is structural spatial interaction in the market and

[18] See LeSage and Pace (2009) for a thorough discussion of the interpretation of parameter estimates in spatial models.

[19] We considered both ways to incorporate spatial effects into a regression model: the spatial-lag model and the spatial error model. These two model specifications are closely related mathematically, but each has a different economic interpretation. As Kim et al. (2003) and Anselin (2001) point out, the spatial error model is appropriate when there is no theoretical or apparent spatial interaction and the modeler is interested only in ''correcting the potentially biasing influence of spatial autocorrelation, due to the use of spatial data''.

[20] As we do not have annual data for air or noise contours (limited time series) the spatial Durbin model is not assessed.

the modeler is interested in measuring the strength of that relationship, for example, as in the spatial reaction function. As Kim et al. (2003) further contend[21], the SLM is equally relevant when the modeler is interested in measuring the ‘‘true’’ effect of the explanatory variables, after the spatial autocorrelation has been removed. This is also endorsed by Anselin and Bera (1998) who state that the spatial-lag model provides the only way to obtain a consistent estimator for the parameter needed to carry out the spatial filtering.

Indeed, whilst the purpose of this paper is not to critique these ‘spatial’ methods, they are used to control for structural characteristics, neighbourhood and accessibility parameters, spatial dependency and spatial heterogeneity. This ensures stability and consistency in the findings to account for the presence of spatial effects and potential missing spatial variables and spatial trends.

OLS (Spatial Regime) Model

As standard economic theory does not suggest an appropriate functional form to be used in hedonic price equations there is limited theoretical guidance for the choice of functional form, since it represents an equilibrium price schedule determined in the marketplace by the interactions of many buyers and sellers. In the absence of clear guidance, it is appropriate to test several functional forms and utilize a multiple regression equation. Cropper et al. (1988) found that simpler functional forms for the hedonic price function performed best when some attributes of housing are unobserved by the researcher or measured with error and employ a semi-log functional form. In this regard, this research employs both the standard OLS fixed effects linear and natural log ($\log_n$) of price. The Multiple Regression equation takes the form:

$$Y = a_o + b_1 x_1 + b_2 x_2 + \ \dots + b_n x_n + \varepsilon$$

Where; a_o - *Is the Regression Constant;* $b_1 \dots b_n$ - *Are the Regression Coefficients; and* ε *is the Error term.* The basic objective of multiple regression analysis is to develop a strong predictive relationship between property characteristics and value, so that the latter can be estimated through knowledge of the former.

The semi-log linear fit is applied within the modelling frameworks due to computational efficiency and interpretability which provides useful interpretations of the independent variable coefficients in terms of their elasticity in respect to the dependent variable. The semi-log specification is as follows:

$$LnY \ = \beta_0 + \beta_1 . X_1 + \beta_2 . X_2 \dots\dots \ \beta_n . X_n + \varepsilon$$

Where; *LnY* is the dependent variable (log of sale price), X_1......X_n are the independent variables; B_0 ....β_n are parameters to be estimated; with ε the error term.

To evaluate the percentage effect, a variation of the equation suggested by Halvorsen and Palmquist (1980) for the semi-log model specification is applied. They point out that unlike a continuous variable, the coefficient of a dummy variable, multiplied by 100, does not represent the usual percentage effect of that variable on the dependent variable. Transformation of the equation applying equation 4 captures the true percentage change:

$$[1 - \ e^{bn}]$$

The estimated true percentage effect of a dummy variable is therefore equal to:

[21] See Kim et al. (2003) for a full discussion.

$$100(e^{bn}-1) \text{ or } g = \exp([\alpha]) -1,$$

Where; the relative effect on the dependent variable of the presence of the factor represented by the dummy variable bn.

Geographically Weighted Regression Model

Geographically Weighted Regression has become a mainstream spatial modelling approach within house price analysis. Typically, GWR has been used across a litany of research studies examining spatial (temporal) variations in market pricing as a consequence of both neighbourhood and locational factors. GWR is represented by the following formula as outlined by Fotheringham et al. (2002:61):

$$y_i = \beta_0(x_i, y_i) + \sum \beta_k (x_i, y_i) x_{ik} + \varepsilon_i$$

where: y_i = i^{th} sale; β_0 = model intercept; β_k = k^{th} coefficient; x_{ik} = k^{th} variable for the i^{th} sale; ε_i = error term of the i^{th} sale; (x_i, y_i) = x,y coordinates of the i^{th} regression point

The approach allows coefficients to vary continuously over the study area, and a set of coefficients can be estimated at any location – typically on a grid so that a coefficient surface can be visualised and interrogated for relationship heterogeneity. GWR makes a point-wise calibration concerning a 'bump of influence': around each regression point where nearer observations have more influence in estimating the local set of coefficients than observations farther away (Fotheringham et al. 1998). In essence, GWR measures the inherent relationships around each regression point i, where each set of regression coefficients is estimated by weighted least squares. Within this study, the weighting scheme Wi is calculated with a kernel function based on the proximities between regression point i and the N data points nearby. A number of kernel functions can be used for the weighting scheme, a plethora of kernel densities which can be implemented which can have varying impact upon ratio study performance[22]. In GWR, an nXn spatial weights matrix is constructed to indicate the weight applied to each observation, assigned relative to the subject based on geographic distance:

$$w_{ij} = exp[-d_{ij}/b^2]$$

where: w_{ij} = weight applied to the j^{th} property at regression point i; d_{ij} = geographical distance in kilometres between regression point i and property j ; b = geographical bandwidth.

The bandwidth in GWR specifies the radius of the weighting function which is either fixed, based on absolute distance, or adaptive - fluctuating, based on a predetermined number of nearest neighbours. An optimum bandwidth can be found by minimising some model goodness-of-fit diagnostic (Loader, 1999). This study utilises the Akaike Information Criterion (AIC) (Akaike, 1973), which accounts for model parsimony (i.e. a trade-off between prediction accuracy and complexity). Within the confines of this research, an adaptive geographical bandwidth of the 40 nearest neighbours was identified as optimal, with an exponential kernel weighting distribution function employed.

Spatial Lag Model

We estimate a hedonic function in log-linear form and test for the presence of spatial autocorrelation and estimating specifications that incorporate spatial dependence, which captures both the direct and indirect effects of a neighbourhood's housing attributes that are inherently spatial in nature such as noise and air pollution. In this study, SLM is more preferred to other spatial hedonic models such as spatial error model

[22] See Gollini et al. (2013) and Bidanset and Lombard 2014b for a full discussion.

(SEM) for two main reasons. First, it avoids the statistical problems arising from inconsistent and biased estimators if spatial autocorrelation is present but not sufficiently accounted for. Second, diagnostic results of some seminal studies in the literature (Kim, 2003) suggested that SLM is the more favoured specification over other ways of spatial modelling (e.g. SEM) for studying the effects of public goods such as air quality on property prices. In this regard, we follow the work of Anselin (1988) and Kim (2003) and distinguish between spatial dependence in the form of a spatially lagged dependent variable. Formally, the SLM is expressed as:

$$y = \rho W y + X\beta + u$$

where y is a n × 1 vector of observations on the dependent variable, X is a n × k matrix of observations on explanatory variables, W is a n × n spatial weights matrix, u a n×1 vector of i.i.d. error terms, ρ the spatial autoregressive coefficient, and β a k×1 vector of regression coefficients.

An alternative interpretation is provided by focusing on the reduced form of the spatial lag model:

$$y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} u$$

where, under standard regularity conditions, the inverse $(I - \rho W)^{-1}$ can be expressed as a power expansion:

$$(I - \rho W)^{-1} = I + \rho W + \rho^2 W^2 + \ldots.$$

The reduced form thus expresses the house price as a function not only of the own characteristics (*X*), but also of the characteristics of neighbouring properties ($W X$, $W^2 X$), albeit subject to a distance decay operator (the combined effect of powering the spatial autoregressive parameter and the spatial weights matrix). β is often described in the literature as "own-region partial derivatives" that captures the "direct effect" arising from *X*, whereas ρ is treated as the cumulative cross-partial derivative measuring the "indirect effect" stemming from *y* through *W* (Lesage 2014). In addition, omitted variables, both property-specific as well as related to neighbouring properties are encompassed in the error term[23]. In essence, this reflects a scale mismatch between the property location and the spatial scale of the attributes that enter into the determination of the equilibrium price.

This study develops a series of models in order to test the effects of the vector of air and noise pollution parameters. We employ a SLM without spatial lags which initially specifies the basic model. However, given the theoretical grounds that the price of a particular property is a consequence of the prices and characteristics of nearby homes, we incorporate and test for the significance of a spatially lagged dependent variable corresponding with the operation of housing markets. Initial modelling examined a set of spatial weights matrices (e.g. $W_{i,j} = 1/d_{i,j}$ and $W_{i,j} = 1/d_{i,j}^2$) in order to obtain the best 'goodness of fit'. The spatial weights approach $W_{i,j} = 1/e^{d_{i,j}}$ produced the best goodness of fit and the results on other key independent variables were largely consistent across the different weighted models therefore was selected. The initial model is re-run incorporating a weighted structure $W_{i,j} = 1/e^{d_{i,j}}$ which uses the average of spatial lagged price information of other properties, thereby accounting for spatial dependencies in the residuals[24]. This spatial lag model is as follows:

[23] For a full discussion see Anselin, L. and Lozano-Gracia, N. (2008) Errors in variables and spatial effects in hedonic house price models of ambient air quality, *Empirical Economics*, *34*(1), 5-34.
[24] Hence the SL residuals should not be distinguishable from random noise.

$$\mathrm{P_i} = W_{exp}\mathrm{P}_j + constant + Area + Appartment + Terraced + \mathrm{detached} + \mathrm{Pre1919} + \mathrm{Interwar} + \mathrm{Postwar} + \mathrm{Early_{moder}} + \mathrm{Elect_{heat}} + \mathrm{Gas_{heat}} + \mathrm{Oil_{heat}} + \mathrm{Private} + \mathrm{Garage} + \varepsilon$$

Where $W_{exp}(\mathrm{In})\mathrm{P}_j = \sum_1^{2500} \mathrm{W_{i,j}P_j}$ [25] and $\mathrm{W_{i,j}} = 1/e^{d_{i,j}}$, $d_{i,j}$ denotes the Euclidean distance between property i and property j.

Incorporating the pollution characteristics (such as NO_2) into the framework gives:

$$\mathrm{P_i} = W_{exp}\mathrm{P}_j + NO2 + W_{exp}\mathrm{P}_j * NO2 + constant + Area + Appartment + Terraced + \mathrm{detached} + \mathrm{Pre1919} + \mathrm{Interwar} + \mathrm{Postwar} + \mathrm{Early_{moder}} + \mathrm{Elect_{heat}} + \mathrm{Gas_{heat}} + \mathrm{Oil_{heat}} + \mathrm{Private} + \mathrm{Garage} + \varepsilon$$

Where: $W_{exp}(\mathrm{In})\mathrm{P}_j = \sum_1^{2500} \mathrm{W_{i,j}P_j}$; denotes a weighted average of spatial lagged price information of other properties $\mathrm{W_{i,j}} = 1/e^{d_{i,j}}$, $d_{i,j}$ denotes the Euclidean distance between property i and property j. and $(W_{exp}\mathrm{P}_j * \mathrm{NO_2})$ is the interaction term, which tests whether the variation of spatial autocorrelation in house prices depends on the level of $\mathrm{NO_2}$.

Results and discussion

This section analyses the findings emanating from each spatial method adopted. For the OLS approach incorporating spatial wards as dummy variables, the structural characteristics for both model forms exhibit all coefficients to conform to expectation, in terms of significance and direction (Table V)[26]. When examining the air quality coefficients for NO_2, the linear model shows low air quality to comprise a statistically significant negative association with house prices (β = -£5,460, p<.05). Conversely, in areas of high and very high air quality house prices are positive with the *very high NO_2* coefficient showing a considerable increase in value (β = £29,830, p<.001), a similar finding is observed for the log-linear model. The results indicate that areas with *low* air quality show a reduction in property prices of 6.39%, with areas of *high* air quality increasing value by 5.13% and areas with *very high* air quality increasing value by 41.76%, all of which are statistically significant. Whilst enormous in terms of the effect on prices, the *very high* air quality coefficient is arguably explained as a consequence of areas in Belfast market with high property prices habitually located in leafy suburbs with large plot sizes and high quality of life – perhaps a 'clean premium' echoing the 'quiet premium' suggested by Theebe (2004). With regards to the particulate matter coefficient ($PM_{2.5}$), both model specifications show the lower $PM_{2.5}$ values to comprise a positive impact on value (β = £6,569, p<.001; β = 6.29%, p<.001), suggesting that higher priced properties are located in areas of lower particulate matter pollutants. Interestingly, the findings show an increasing negative impact on houses above the micrograms of contaminant per cubic meter range threshold of $10PM_{2.5}$. The linear model however only signifies the range (11.01-12) to be statistically significant at the 1% level. In contrast, the log-linear coefficients, with the exception of the

[25] $W_{exp}\mathrm{P}_j$ Indicates a weighted average of spatial lagged price information of other properties.

[26] Spatially delineated wards available upon request

10.01-11PM$_{2.5}$ parameter achieve statistical significance, illustrating a -9.34% to -11.13% impact on property prices.

Turning to the noise coefficients, it is noteworthy that road noise across all ranges in both models are statistically insignificant (p>.05), thereby inferring that road noise does not seem to impact upon property prices in the Belfast housing market. However, in terms of the proximal effect, the results point towards an inverted quadratic pattern consistent with a positive longer-range distance–decay accessibility effect minus a smaller and shorter-range distance–decay disamenity effects in line with Li and Saphores (2012). The coefficients are nevertheless insignificant at the 5% level, with only the distance buffers (225 metres and 250 metres) significant for both models. The findings show that residing in proximity to a major arterial route above 225 metres or 250 metres distant increases property prices by £7,514 or 5.65% (p<.001) and (£4,801 or 3.77%) respectively.

The rail noise and proximity findings show a mixed picture and elements of counter-intuition in the coefficient values, direction and significance. The *low rail noise* coefficients reveals a negative impact on value (β = -£4,130, p<.001; β = -4.06%, p<.001), suggesting that rail noise reduces house prices. As expected, *the high rail noise* estimate also commands a negative pricing effect (p<.05), indicating that the presence of high noise from railways negatively impacts on house prices to a sizable degree (β = -£24,811, p<.05; β = -30.58%, p<.001). In terms of adjacency, properties located within 250 metres of a railway seemingly are negatively impacted in terms of their prices when scrutinising the linear OLS model, however only the distance bands up to 125m are significant at the 10% level. The log-linear model shows the distance bands (100m and 200m) to be statistically significant (p<.05) commanding a negative price effect of 9.79%, a finding in accordance with previous research undertaken by McCord et al. (2018) investigating the proximal effects of neighbourhood amenities within the Belfast housing market. In interpreting these figures it must be noted that the Belfast suburban rail network is rather limited in scale and its particular routing is associated with predominantly lower value terraced and social housing, particularly in its northern and eastern branches.

When considering the noise impact of airports, the coefficients are all statistically insignificant for both model specifications despite exhibiting an increasing negative effect from low to high decibels. When considering proximity, a similar picture emerges. All distance coefficients are negative inferring that adjacency to the nearest airport reduces house prices, however, only two distance bands are statistically insignificant (1,501-2000 metres; 2,001-2,500 metres). The results therefore seemingly suggest that whilst there appears both a distance decay effect and noise pollution impact, the results are more spurious tending to be insignificant (p>.05). In terms of industrial noise and proximity, the base noise coefficient displays a negative value for both models significant at the 10% and 5% level, suggesting that proximity to industrial locales detracts from property prices. This is also evident when scrutinising the proximity effect, as reflected by the significant negative coefficient *Industrial distance400* which indicates properties located within 400 metres of industrial zones in Belfast reveal a price reduction of 8% (p<.001) or -£7,161 (p<.001). Nonetheless, these findings must be caveated given the strong historical existence of the port area and associated road structures of the Belfast geography. The traditional and long-standing manufacturing industry and accompanying housing remains archetypical of the housing market structure (small, old terrace properties) adjacent to these zones which will fundamentally impact upon the price ceiling and the reduction of housing prices as benchmarked against normal market structure and pricing levels.

<<<<<<Table V OLS Linear and Log-Linear Models>>>

Geographically Weighted Regression Model

The conditional mean estimates within the OLS models highlighted some important findings; however, they do not allow the estimates to fluctuate across the urban plain. As a result, heteroscedasticity, or spatial heterogeneity inherent in the property price data may also represent differences in the urban environment which need to be modelled more reliably by the spatially varying GWR coefficients. The GWR model is applied in order to account for spatial heterogeneity and allow the housing and pollution characteristics to vary over space thereby providing spatially derived marginal prices. With regards to the structural property attributes, the interquartile range of the coefficient estimates are of plausible magnitude, with limited maximum and minimum values displaying extreme or counter intuitive results, with the exception of the DET (detached properties) coefficient (Table VI). The minimum value coefficient suggests that, all else equal, a detached property sells for 37.5% less than a terrace property at one observation and 62% higher at another. Nonetheless, this value whilst excessive on first viewing, could be attributable to what is a relatively heterogeneous market setting where large traditional three storey terrace properties with period features are located in very desirable locations.

Indeed, as displayed in Figure III, the structural characteristics show considerable spatial effects in terms of their coefficient values, revealing property size, type and age to vary significantly across the Belfast housing market.

<<<Figure III Structural coefficients spatial representation>>>

With regards to the NO_2 air quality coefficient (Figure IV), the findings reveal an interesting spatial depiction across the coefficient range illustrating both positive and negative effects. The *Low air quality* estimates show significant variation remaining negative until the 3rd quartile of the coefficient value, thereby inferring that low air quality (high levels of NO_2) impact negatively upon prices, with the exception of well-established upmarket housing areas towards the South- South East of the city reflective of the utility trade-off between level of air pollution and desirable living locales. Indeed, across all air quality measures the findings show negative coefficients at the 1st quartile, illustrating that even in areas of high air quality property prices suffer from wider market and environmental concerns. What is interesting to note is that the coefficient values are positive at the market median for *high air quality* and *very high air quality* areas which show an increasing positive impact between these ranges – suggesting that higher priced properties ‘value’ air quality more highly. Combined with the negative signs at low value areas, this suggests a cubic relationship. An interesting finding in this regard pertains to the spatial patterns characterised by higher values in the south west of the city where low air quality negatively impacts on house prices, and high and very high air quality positively impacts on house prices. This pattern is a likely consequence of topography and prevailing winds. Low air quality high value areas remain unaffected whereas the rest of the market appears more anaemic, however when examining the spatial variation of the high air quality this appears to impact positively on the market, albeit at different pricing levels, notably advantaging higher value areas.

<<<Figure IV No_2 Air Quality Spatial Representation>>>

With regards to the $PM_{2.5}$ air quality parameter, some extreme values exist. For example, the estimates for $PM_{2.5}$ ranging between, 12.01-13$PM2.5\mu g/_{m^3}$, show the coefficient values to differ by -74.7% and

+101% in some areas when accounting for high particle matter (poor air quality). What is noticeable however is the direction of the coefficient values when observing the particle matter ranges. At the 1st quartile, $PM_{2.5}$ shows a positive effect on house prices until the range greater than 11 $PM2.5\mu g/_{m^3}$, inferring that higher levels of $PM_{2.5}$ have a negative impact on house prices (12.01-13.0 $PM2.5\mu g/_{m^3}$ = -6.27%), whereas lower levels of $PM_{2.5}$ have an increasing positive effect (8.01-9.0 $PM2.5\mu g/_{m^3}$ = 14.6%). In addition, the parameter estimates exhibit lower percentage effects on value at the median and 3rd quartile range for the higher levels of particle matter, suggesting that lower levels of $PM_{2.5}$ pollution have a higher positive association with house prices, and higher levels of $PM_{2.5}$, albeit it positive, a lower effect. The results show air quality to have a spatial impact on house prices, however, they do intimate that across the value distribution this is not a simple effect. Arguably the results capture the variation across the urban landscape and market pricing structure for localised demand and supply tastes – for clean air, and the resulting spatial heterogeneity. For example, apartments located in the city centre region which may suffer from high levels of $PM_{2.5}$ pay more for exclusivity and the trade-off for transport friction costs, city centre living and air quality. They may well enjoy a height advantage and increased wind speed which ameliorates the effects of ground level pollution – a ‘z’ co-ordinate and distance altitude distance decay statistics would be required to determine this however. Interestingly to the East of the city, the spatial representation of higher levels of particulate matter also show paradoxical results with house prices as highlighted in Figure V. Nonetheless, there is a consistent spatial depiction which reveals evidence of market segregation between the north-east of the harbour region and east of the city relative to the south-west area of the Belfast market, where the former across the PM2.5 levels are continuously negative, with the latter being positive.

<<<Figure V $PM_{2.5}$ coefficient spatial representation>>>

In terms of the road noise parameter estimates, the findings show no decisive patterns or relationships - both across the noise ranges (low to extreme) and the coefficient values 1st – 3rd quartiles) of the properties, similar to the OLS results (Figure VI). This is also evident for the distance-decay effect with regards to proximity to roads. The spatial variation for road noise displays both negative and positive impacts in different parts of the city and demonstrates counterintuitive results, changing across the city for low, moderate and high road noise level dB which does not appear to be continuous. Interestingly, low road noise has a detrimental impact on property value in the more built-up urban environment towards the CBD, with high road noise associated with increasing value. This infers that road noise is not considered a significant externality within the Belfast market. Similar to the findings of Day (2003) for the Glasgow housing market and Duarte and Tamez (2009) for the Barcelona housing market, this is arguably a market premium trade-off between noise level and gaining access to services and transportation rapidly but without suffering the highest levels of noise from the roads on which they are located. It may also imply less concern regarding comfortable use of outside spaces in more urban areas and increasing use of mitigating strategies, such as the installation of high performance double and even triple glazing.

<<<Figure VI Road noise coefficient spatial representation>>>

The rail noise estimate shows a high spatial randomness across the rail noise estimates. The distance coefficients do not reveal a continuous trend highlighting the complexity of proximity and noise of railways as an externality. For properties immediately adjacent to a railway the inter-quartile range is in the main positive until the 200 metre distance band – inferring distance to the railway is a positive externality on house prices. With regards to noise dB, both *low* and *high rail noise* levels show a negative relationship across *all* (inter-quartile) ranges, with the moderate rail noise coefficient only negative at the 1st quartile level. What is noteworthy is the paradoxical finding for the *very high rail noise* coefficient is positive at all quartile ranges, surmising high rail noise to increase house prices as evidenced in the spatial delineation across the rail noise coefficients, where low rail noise dB has the highest positive impact on prices in the city centre (edging south) and towards the corridor heading along the primary arterial route northwards. The increase in rail noise dB exhibits a diminishing effect on properties to the south of the city.

<<<Figure VII Rail noise spatial representation>>>

The airports coefficients display a consistent pattern across the dB ranges, with both the high and moderate noise levels exhibiting a negative influence across the inter-quartile coefficient range. Examination of the coefficient values spatially reveals a number of distinct patterns emerging. There appears to be a segmented market with the North and North-West market unaffected by the distance and noise externality of the city airport. Conversely, the South and South-East display reduced positive and negative association across the coefficient quartiles which become pronounced as the dB range increases arguably as a consequence of the existing flight path which is located directly above the South of the city.

<<<Figure VIII Airport Noise coefficient spatial representation >>>

A flight path effect?

As a matter of interest, and given the rich literature base pertaining to the effect of airplane flight path noise, the research included the created binary variables based on whether the houses fell within the boundary of being directly under the regional airport flight path, and whether the dB levels (categorised as low, moderate or high) impacts upon market pricing. The results show some fascinating findings (Table VII), clearly indicating that flight path noise has a negative impact on house prices which increases the higher the decibel range (-3.95% for moderate flight noise and 7.26% for high flight noise). Moreover, when considering whether a property was directly located under a flight path, the findings show a 5.45% negative effect on house prices (-£6,560), significant at the 5% level. This is evident within the GWR model parameter estimates which also show high and moderate flight noise to comprise a higher negative effect illustrating the spatial variation of the flight noise effect. The positive coefficient value, as displayed by the positive 3rd quartile for properties under the flight path is perhaps reflective of enclaves of higher priced properties and topographical market structure and profiling. Of note is the reality that Belfast is relatively small and compact and lies under the approaches to the regional airport some 17 miles distant. For those not under a direct approach path to the metropolitan airport, aircraft noise may be somewhat generalised and virtually ubiquitous

<<<Table VII Flight Path effect on house prices>>>

Finally, the parameter estimates for the Industry noise and distance externalities suggests that industry noise does impact upon house prices – the effect of which diminishes when considering the inter-quartile range, illustrating high spatial variation.

OLS and GWR Model stability

The models both revealed high levels of explanation, exhibiting a good fit for a number of the key parameters investigated. Indeed, for both models the residual values show that they are (generally) normally distributed, however the GWR model is more proficient with the extreme high and extreme low values as evidenced by reduction in high and low residuals as evidenced in Figure IX. The results do, in particular instances, reveal some evidence of heteroscedasticity in the models, likely associated with spatial autocorrelation and/or non-stationary of the residuals given the spatial clustering for most pollutants and typical housing stock.

<<<Figure IX OLS and GWR residual statistics>>>

Spatial Lag Model

The Spatial Lag approach is employed to take account for any spatial dependence issues and test for the presence of positive adjacency effects. Initially tested accounting for no spatial lag (Model 1), the results show a 54.36% explanation. Factoring in the weighted average of the spatial lagged logarithmic price information of the neighbouring properties (spatial lag term $\mathrm{W}_{\mathrm{i,j}} = 1/e^{d_{i,j}}$), the level of explanation increased substantially (R^2 = 87.4%) as observed in Table VIII (Model 2), with property prices positively correlated over space at the 1% level. This suggests that the price of a subject property is correlated with those in close proximity[27]. Turning to the air pollution variables of interest, examination of the NO_2 coefficient (Model 3) reveals it to have a negative impact on property prices (β = -0.190, p<.001), inferring that the higher the NO_2 level, the stronger the spatial autocorrelation of house prices, as indicated by the positive coefficient of the interaction term ($W_{exp}\mathrm{P}_j * \mathrm{NO}_2 = 0.017$). This indicates that, if NO_2 is higher, property prices tend to be more correlated spatially. Moreover, the results also exhibit $PM_{2.5}$ ($PM2.5\mu g/_{m^3}$) to comprise a negative effect on house prices as property prices become more spatially (auto)correlated as $PM2.5\mu g/_{m^3}$ levels increase. The findings from the SLM's strongly suggest that air pollution parameters negatively impact on property prices where levels are high and in a spatially correlated fashion.

<<<Table VIII Spatial Lag Models>>>

With regards to the effects of noise pollution, three further SLM's have been constructed (Table VIII: Models 5-8). The rail noise coefficient is negative illustrating it to comprise a statistically significant effect on property prices (β = -0.908, p<.001), and indicating that the higher the noise level, the stronger the spatial autocorrelation of house prices, as displayed by the positive coefficient of the interaction term $W_{exp}P_j * \ Rail$. Examination of both the airport and road noise coefficients and their associated spatial interaction terms show statistical insignificance, thus demonstrating limited meaningful conclusion can be drawn about these noise variables on property prices. Overall, the SLMs shows high explanatory power across the various pollution based models developed and high explanation accounting for the spatial structure and dependence of the pollution based parameters. The coefficients of the lag term within all Spatial Lag Models suggest that house prices in Belfast are spatially autocorrelated. The positive signs of the coefficients signify that high (low) prices tend to cluster over space, with the presence of NO_2, $PM_{2.5}$ and rail noise tending to increase the spatial autocorrelation of house prices exhibiting statistically significant negative outcomes with property prices. In other words, prices of properties that are affected

[27] We follow the process of Wong et al. (2013) which used spatial lag to determine spatial autocorrelation. For a full discussion see: Wong, S. K., C. Y. Yiu., and K. W. Chau.(2013) Trading Volume-Induced Spatial Autocorrelation in Real Estate Prices, The Journal of Real Estate Finance and Economics, 46(4), 596–608).

by these pollutants are more spatially correlated, confirming the importance of those pollutants. Surprisingly, airport noise and road noise do not have a statistically significant impact on market pricing.

In summation, the findings from across the three differing hedonic approaches accounting for spatial effects present consistent results. Poor air quality as depicted by nitrogen oxide and particle matter both comprise a detrimental effect on house prices which are shown to cluster in a spatially varying manner. The OLS model illustrated that both air quality measures show poor air quality to reduce the pricing of property, with good (high) air quality increasing prices. This was also observed in the GWR parameter estimates where, until the 3rd quartile of the pricing distribution, the same negative effects were observed. Interestingly, the varying nature of the GWR approach illustrated that the spatial heterogeneity with the market structure does impact on the level of impact of the air quality measures. Pertinently, the results exhibited lower priced properties are affected more by poor air quality with higher valued properties valuing air quality more highly. This was confirmed by the SLM model which revealed air quality and house prices to cluster spatially with higher (or lower) pollution levels autocorrelated with increases (or decrease) in house prices.

This is also the case for the rail noise parameter, which demonstrates a more complex spatial representation, a finding evidenced across all model specifications. The OLS (linear and semi-parametric) coefficients revealed an effect evident, however this varied in magnitude and statistical significance with distance proximity reflecting a complicated and inverted trade-off between noise levels and distance up to 125m proximal to the rail hub amenity. The GWR findings also displayed this complex depiction and reveals a more spatial random and discontinuous distance effect. Akin to the OLS estimates, distance to the railway appears to act as a positive externality on house prices. This is confirmed by the SLM which furnishes evidence of spatial autocorrelation and rail noise. With regards to road noise the OLS, GWR and SLM all show statistically insignificant effects across all spatial frameworks. Interestingly, the OLS revealed that proximity the arterial roads plays a role in pricing, albeit displaying significant coefficients beyond 225 metres. In a similar vein, the GWR revealed that road noise shows no continuous trend, no capitalisation effect reflective of any utility trade-off between noise and accessibility (walkability), a finding exhibited in the SLM which presents no meaningful evidence of road noise and house prices and no validation of autocorrelation.

Conclusions

There exists a volume of research which has isolated the specific effects of air and noise pollutants on property prices using a variety of spatial modelling approaches. The paper has added to this literature base by conducting analysis into the effects of air quality and noise disturbance and proximity on property prices in the Belfast housing market. The research combines analysis of a larger number of environmental effects, using three differing spatial modelling methodologies, to ensure consistency in the results, robustness in terms of model stability and to adequately account for spatial dependence and autocorrelation of the spatial variability of air quality estimates and noise pollutants, at the intra-urban level in the urban environment. The need to account for endogeneity was apparent, therefore both GWR and Spatial lag models were assessed. The spatial lag specification allowed for a distinction between direct effects and the role of a spatial multiplier through the interaction term. A combination of environmental effects is deemed to be appropriate to avoid missing variable issues – e.g. the measurement of transport pollution without accounting for noise may misallocate the dis(amenity) effect from one cause to another. Indeed, the use of one modelling approach over another leaves questions regarding model form effect. This combined approach seeks to add clarity with regards to what the actual and relative effects of the environment are, and how the market appears to differentially price them.

The OLS provides a strong fit showing individual pollutants to display different degrees of effect and a certain degree of spatial variability. Nonetheless, the GWR yielded more localised spatially varying coefficients, displaying substantial spatial variability and self-similarity over short distances, suggesting that this approach accounts for intra-urban spatial variability of the pollutants. It thereby provides more reliable predictions, as well as a more accurate model of air pollution at the intra-urban levels. The SLM approach showed the (marginally) highest level of overall explanation, whilst lacking the essential 'key' to the modelling 'black box' provided by the GWR map based output which allows locally informed users to identify and supply context to the statistical output. Despite this, the SLM

The findings, across all model architecture, overwhelmingly indicate that air quality seems to have an *asthmatic* effect on property prices. Indeed, Nitrogen dioxide has consistently illustrated a negative relationship across all modelling approaches, with Particle $Matter_{2.5}$ consistently exhibiting an adverse relationship with property prices. Indeed, the results show a consistent relationship between house prices and air pollution (quality) implying perhaps people living in lower priced property (and arguably of lower socio-economic status) are residing in urban environments which are harmful to health and wellbeing, illustrating a compounding effect between the pollutants, distance, pricing and market structure – the capitalisation effect – to coin a phrase, poor air is bad for your health *wealth* and wellbeing. The 'pockets' of good air in more wealthy neighbourhoods appear to benefit from additional gearing effects, ramping up the house price effects more so than in the general mid-market range – suggesting a cubic profile to the pricing effect.

An interesting finding related to the noise and distance from roads. Across the differing spatial models employed, it appears to have no proximal effect or pollution impact for home owners. Noise does appear to be 'in the ear' of the beholder in this regard, appearing to have differential effects depending on source and on specific location. Behavioural factors may well play a part here, with some doubt remaining regarding the effect of the *perception* of noise, when low flying aeroplanes are visible, for example, or when a railway line quite visibly runs in close proximity. A behavioural perspective may shed further light on this phenomena, across all the environmental factors as the market is made up of people with limited ability to perceive the 'true' state of nature – particularly with regard to colourless, odourless pollutants in proximity to perhaps leafy, tree lined areas, with adequate green space and perhaps the views over green hills and expanses of water that Belfast can provide.

Nevertheless, the pricing effects of the pollutants do appear to be evident. The research is therefore important in terms of providing an evidence base for policy regarding liveability and the adverse effects of pollution on public health and wellbeing, particularly in terms of planning interventions in urban environments, such as pollution controls, air traffic limits (such as the ban on night flights and runway extension in Belfast's George Best Airport), congestion charging proposals and urban infrastructure proposals. This paper also contributes greatly to the real estate valuation literature, valuation profession and policy, in that it provides a market transaction price-based empirical assessment of how property values can be spatially affected by the presence of some important pollutant attributes. For example, the findings could serve as a reference for determining the amount of compensation for noise/air pollution impacts on affected communities due to new private or public (re)development projects such as airport expansion and relocation of industrial plants, under the 'polluter pays' principle. Conversely, it may provide useful data in assessing material benefit to home owners of pollution reduction measures, in terms of determining who should pay for such projects, under the 'those who benefit should pay principle'.

The findings provide clear evidence that local air zone management strategies and noise abatement and management strategies need further examination in the Belfast housing market. More specifically, the findings show that particular pollutants comprise a spatially varying difference in terms of their impact upon market pricing and behaviour which is a fundamental issue for policy development and management targeting. Indeed, the results suggest that this offers a basis for identifying a demand function for air quality is a key input to calculate welfare measurements of pollution abatement policies moving forward.

In consolidating these findings future work will seek to utilise data which is envisaged to become available in terms of nuances in air quality data which may permit a difference in difference methodology to be adopted, to more robustly capture the change in pricing and air quality using a two-step hedonic framework. More longitudinal studies are also required to capture the effects of change over time and to examine seasonal variability (e.g., due to seasonal variation in heating or idling vehicles in cold temperature). Future work will seek to address limitations implicit herein: Results are restricted to one urban area, therefore it would be beneficial to compare peri-urban areas to examine or reflect the changing density of housing market and urban form – extending the analysis. Also, a number of aspects of estimation were not taken into consideration and remain the subject of future work. Foremost among these is the role of spatial heterogeneity. The strong evidence of remaining heterogeneity and spatial correlation would suggest that perhaps a different scale of analysis might be more appropriate. For example, this might include an explicit accounting for submarkets or for possible sorting of households by preference regarding environmental quality. Finally, the evidence presented here only applies to a single case study, and additional empirical work is needed to start establishing the foundations for general results.

Of particular concern, leading from the findings of this research, it is hoped that accounting for errors in variables of the interpolated pollution measures will become a routine aspect of applied work in spatial hedonic models of ambient air quality. Poor air demonstrably affects health and wealth outcomes – irritating both the airways and the wallet and therefore by no means a jolly wheeze.

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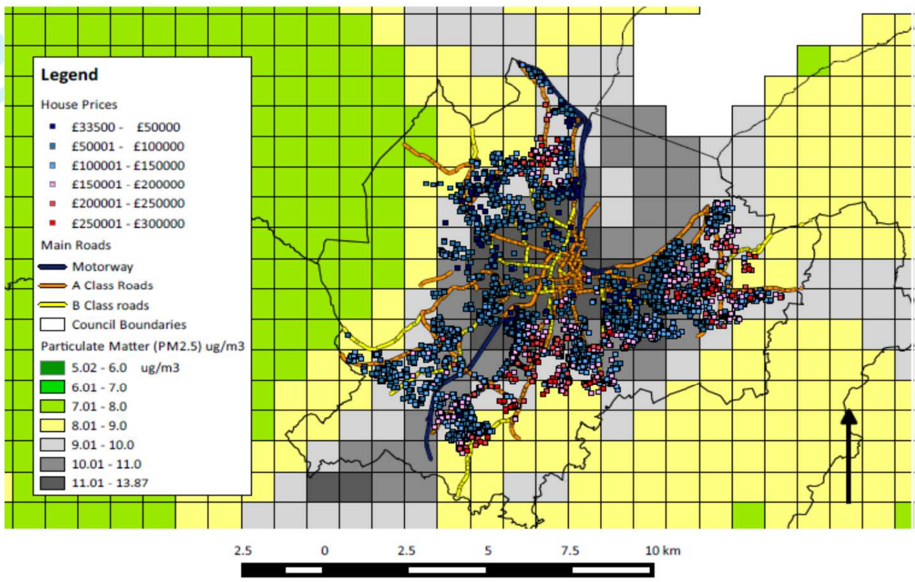
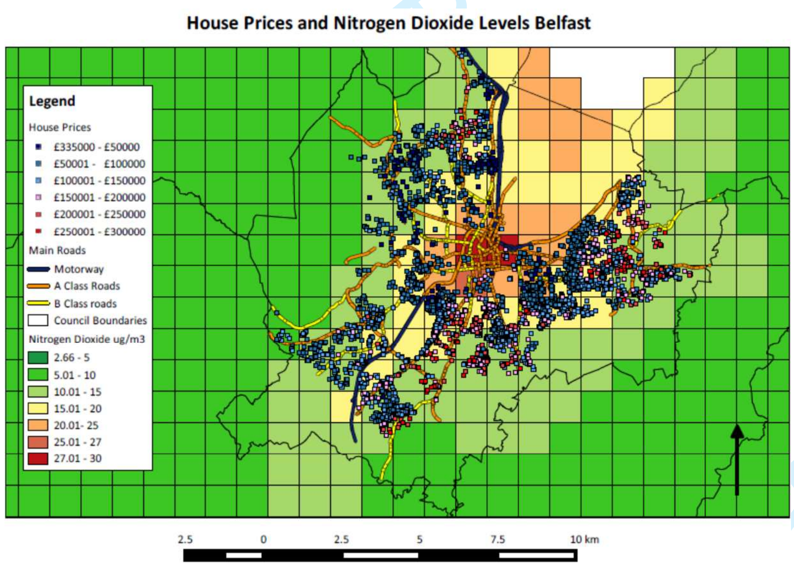
Figures

<<<Figure I House Prices and Air pollution variables>>>

House prices and Particulates level ($PM_{2.5}$)



House prices and Nitrogen dioxide levels



House prices and Nitrogen dioxide AQMA's

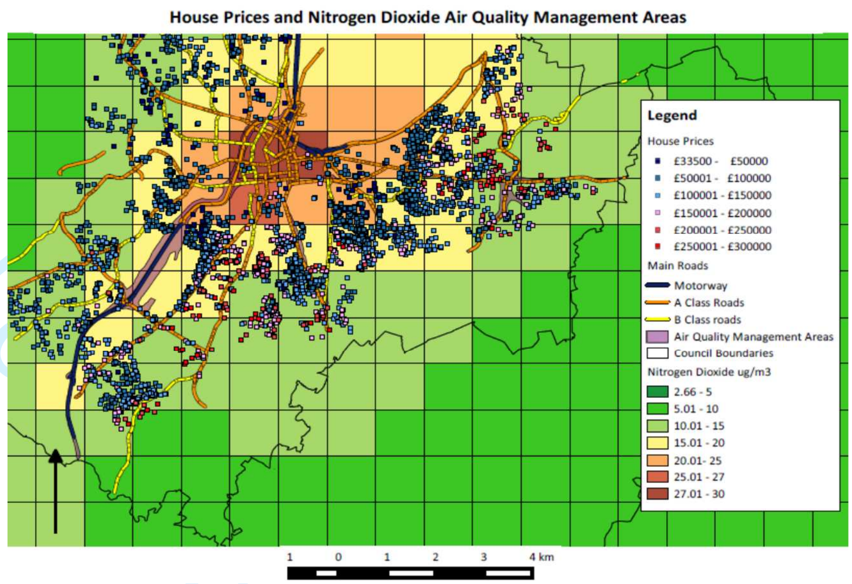
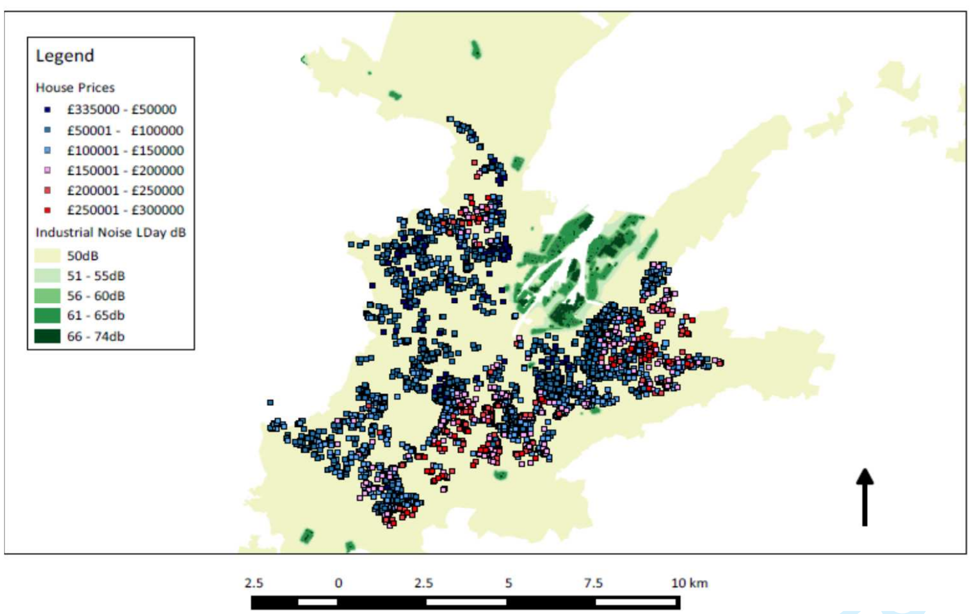
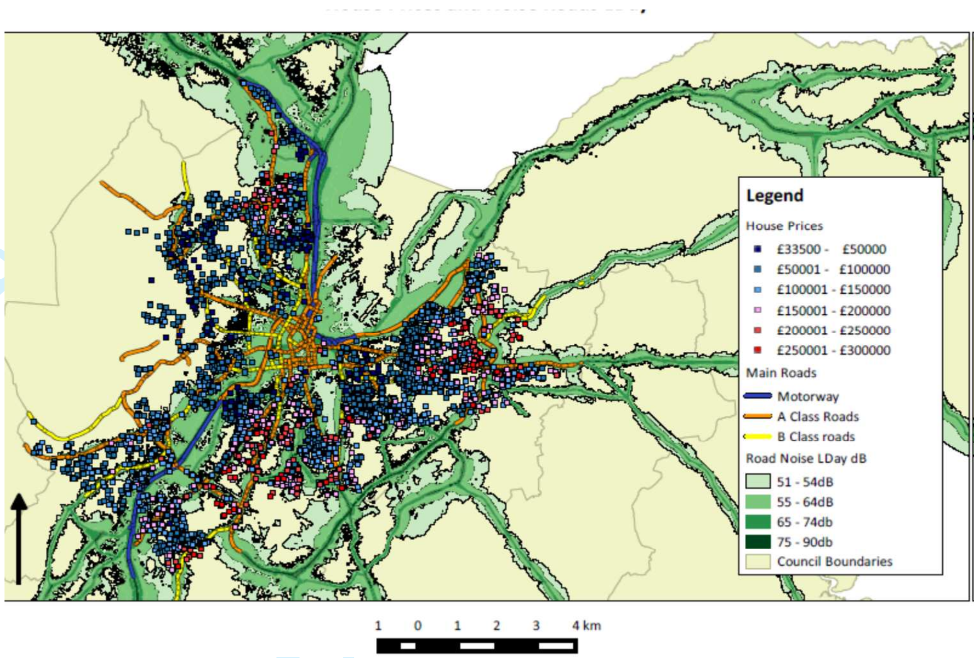


Figure II Noise pollution variables

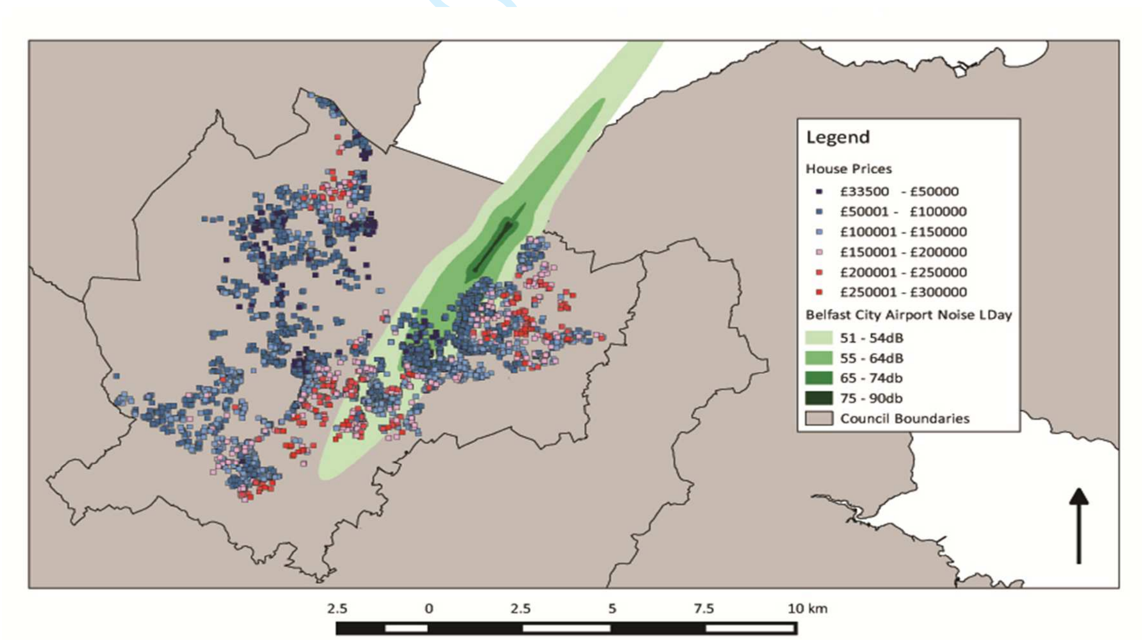
House prices and Industrial noise (dB ranges)



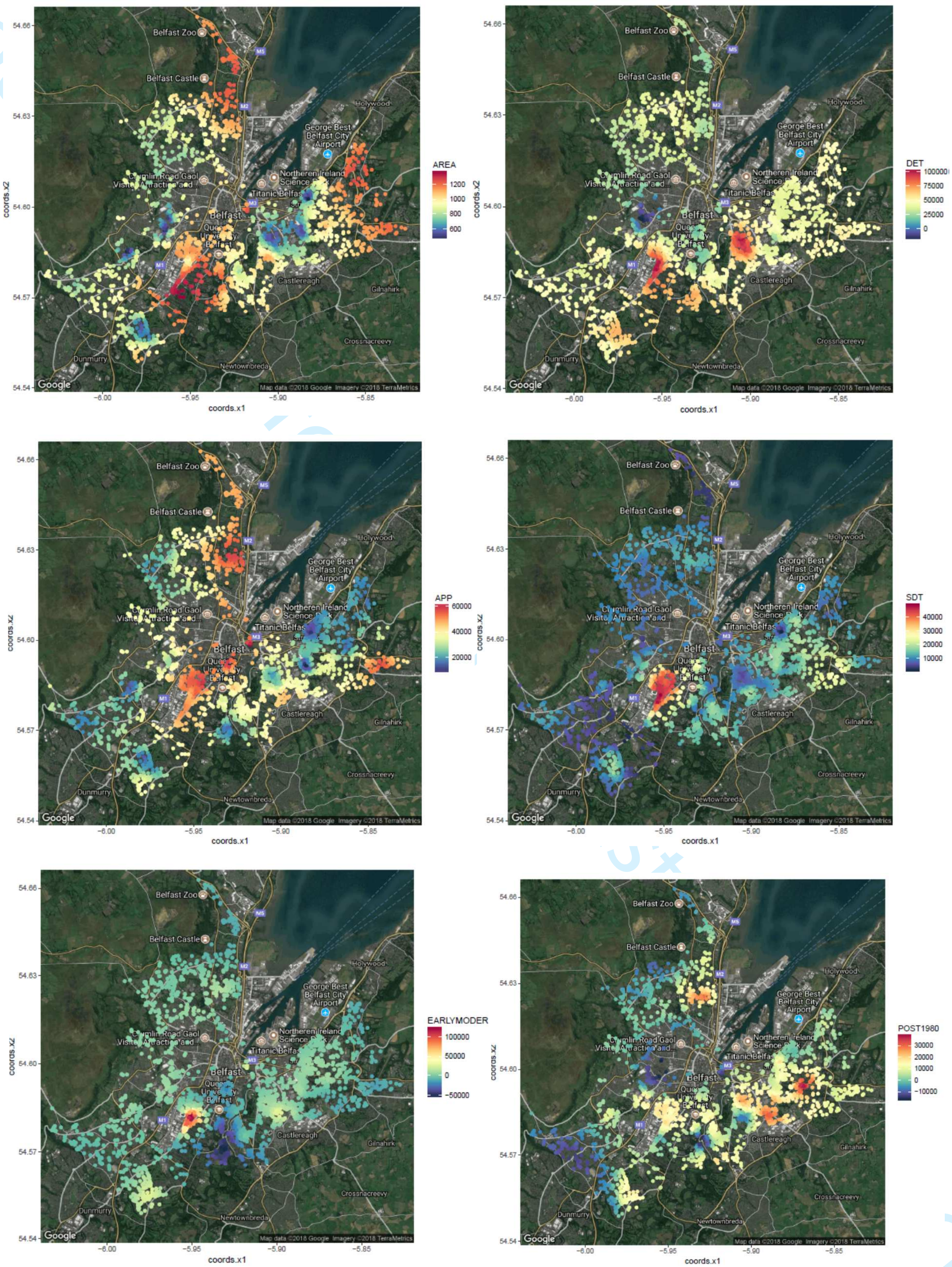
House Prices and Road noise (dB ranges)

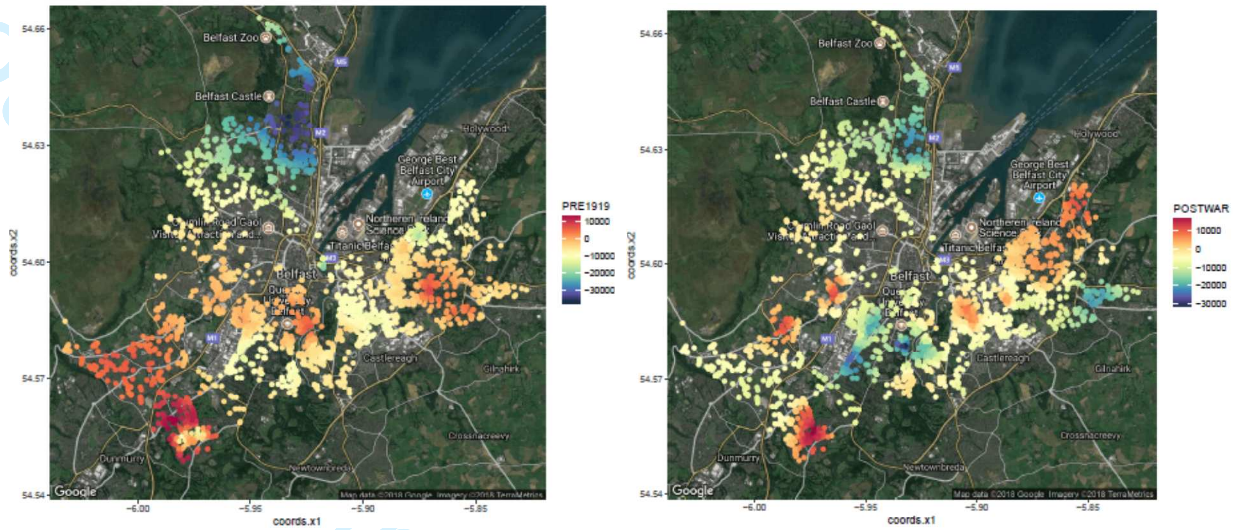


Airport and Flight path noise (dB ranges)

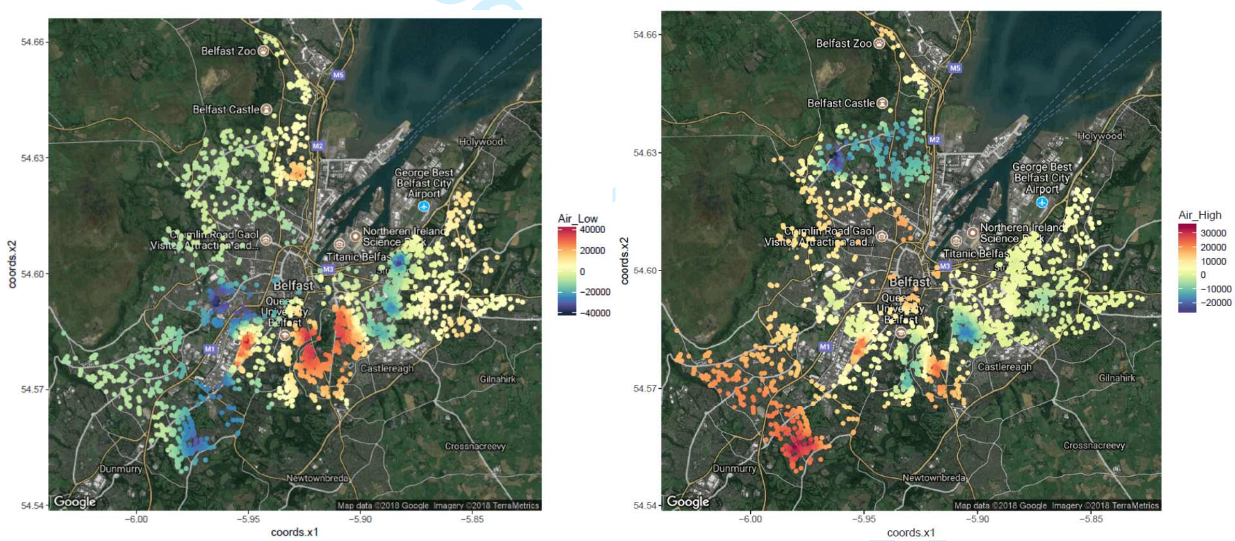


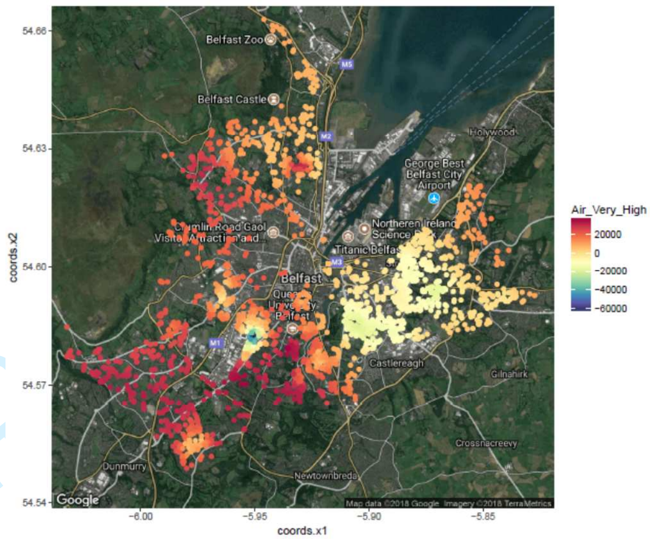
<<<Figure III Structural coefficients spatial representation>>>


AREA
DET
APP
SDT
EARLYMODER
POST1980
coords.x1
coords.x2

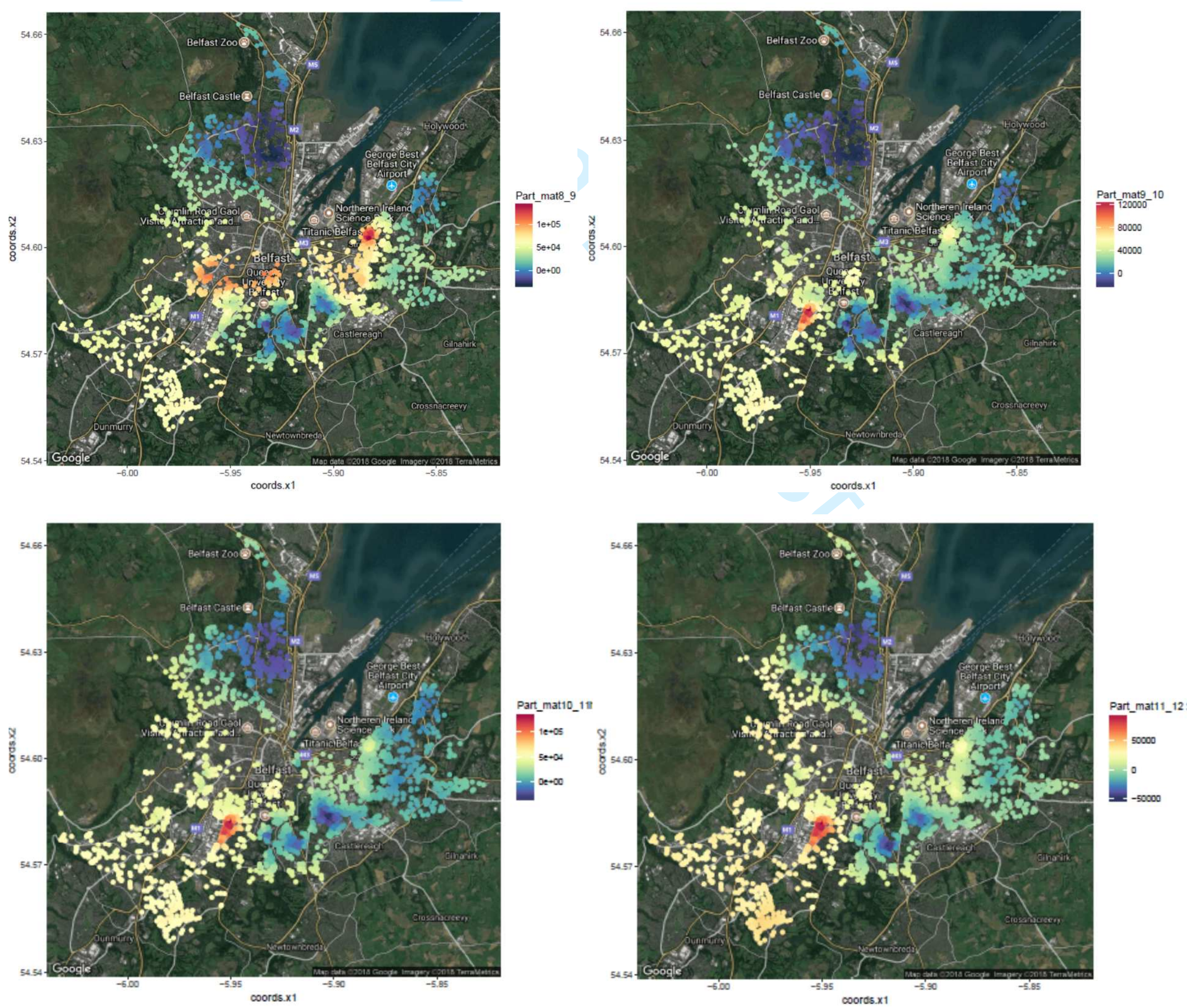


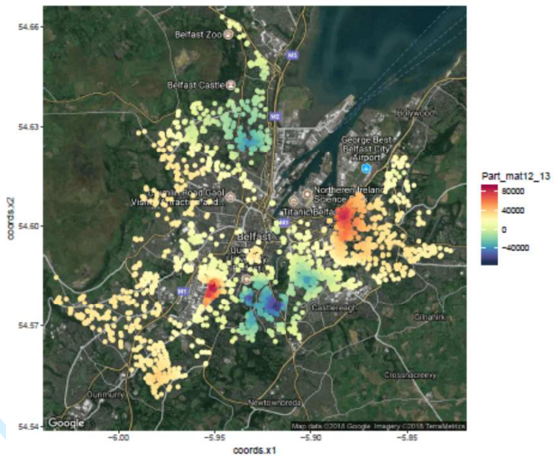
<<<Figure IV No$_2$ Air Quality Spatial Representation>>>



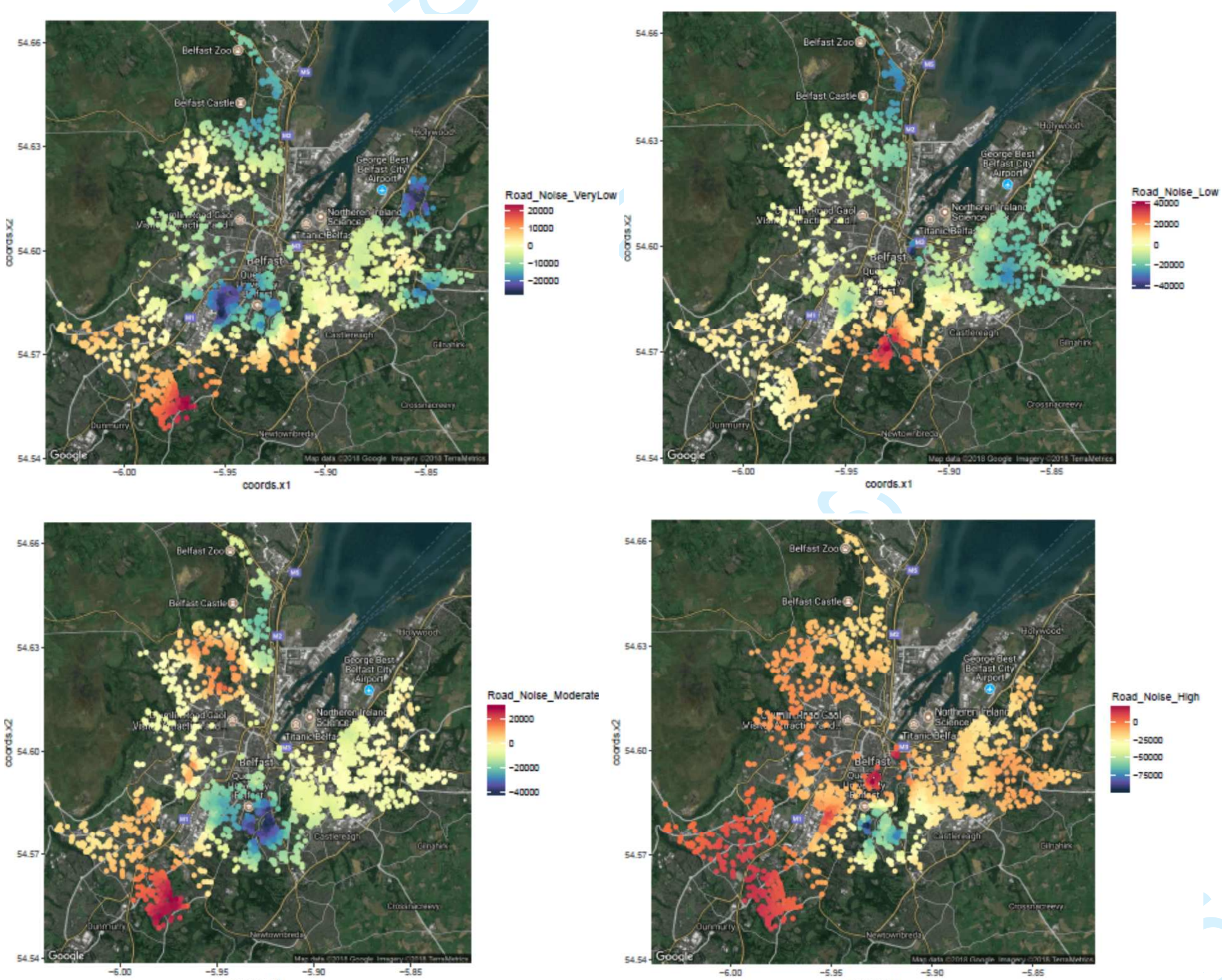


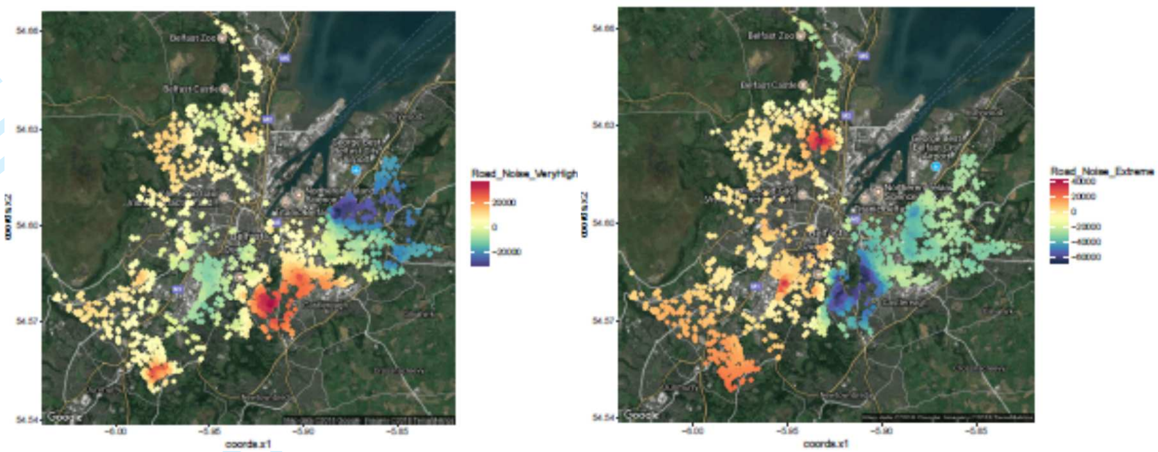
<<<Figure V $PM_{2.5}$ coefficient spatial representation>>>



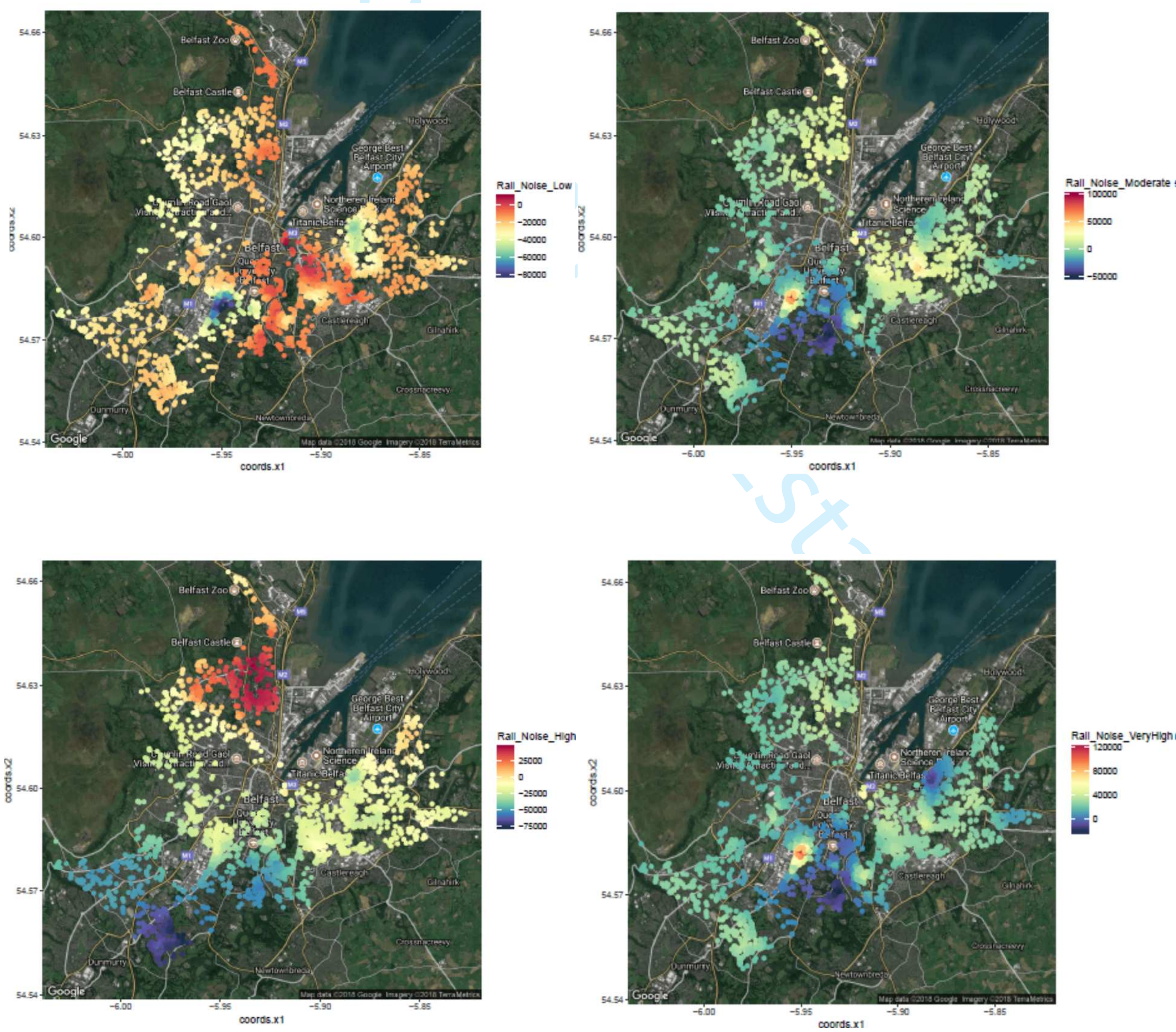


<<<Figure VI Road noise coefficient spatial representation>>>





<<<Figure VII Rail noise spatial representation>>>



<<<Figure VIII Airport Noise coefficient spatial representation>>>

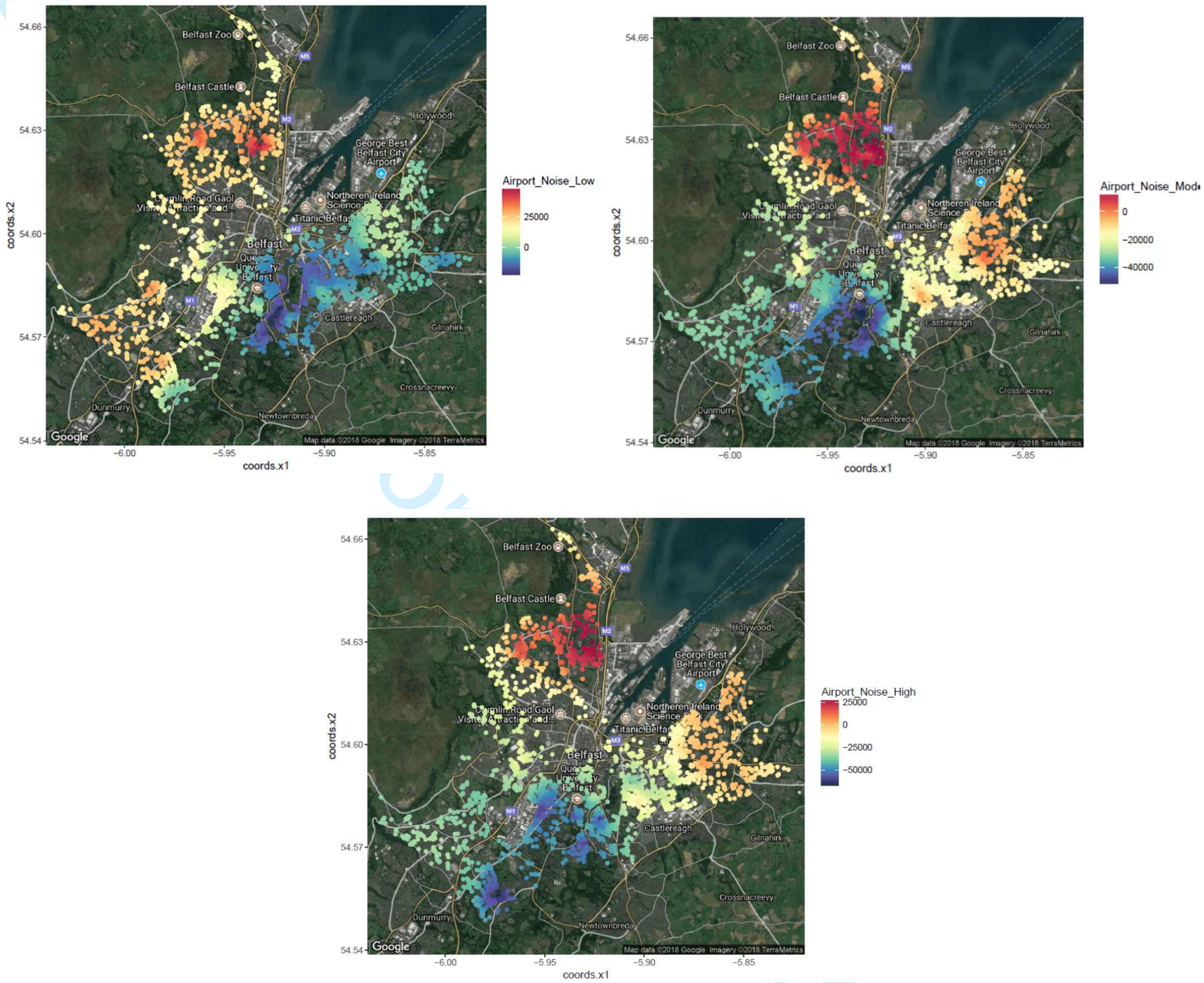
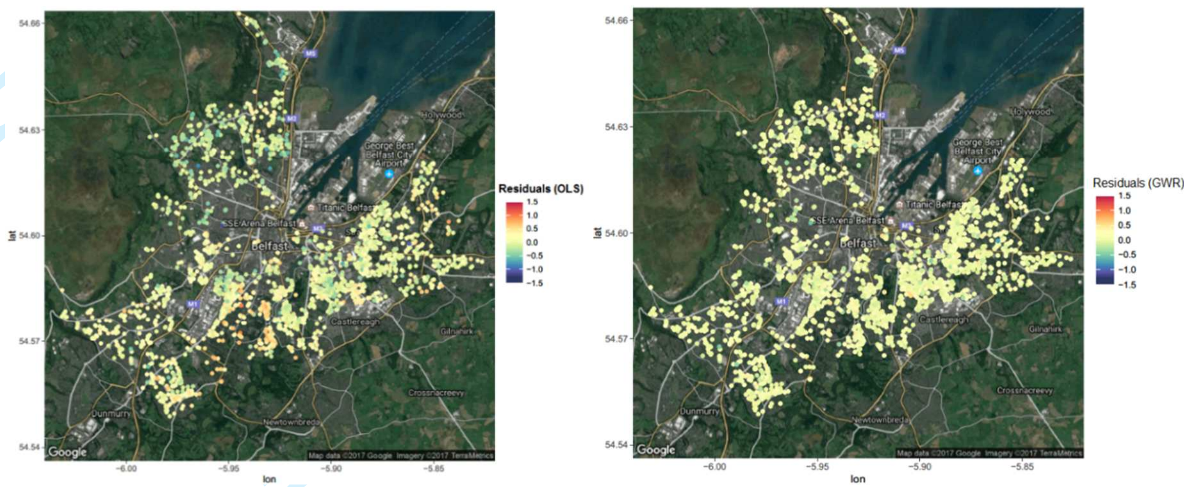


Figure IX OLS and GWR residual statistics



Tables

<<<Table I Air Quality Variable Descriptions>>>

Particulate Matter	Particles emitted directly from combustion processes. These particles are generally less than 2.5 µm and often well below 1 µm in diameter	ug/m^3: micrograms of contaminant per cubic meter. Usually it is referenced at a pressure of 1atm and 25ºC i.e. (one-millionth of a gram) per cubic meter air or µg/m^3
Nitrogen Dioxide (NO2) and nitric oxide (NO)	Oxides of nitrogen and are collectively referred to as NOx. All combustion processes produce some NOx emissions, largely in the form of nitric oxide	ug/m^3: micrograms of contaminant per cubic meter. Usually it is referenced at a pressure of 1atm and 25ºC i.e. (one-millionth of a gram) per cubic meter air or µg/m^3
Air Quality Management Areas (AQMAs)	Environment (Northern Ireland) Order 2002 states local air quality management process and the procedures that district councils should follow when carrying out their duties[1].	Designated Area if in constant breach of regulations

<<<Table II Pollution variables frequencies for sampling adequacy>>>

Attributes	Bands	Range	Observations	%
NO_2	V. High	(7.40-12.97)	386	15.4
	High	(12.98-18.54)	470	18.8
	Mod	(18.55-24.46)	1551	62.0
	Low	(24.47-29.66)	94	3.8

[1] Art 11 of the Order provides that every district council shall review the air quality within its area at the present time and assess the likely future quality. Article 12 requires district councils to designate an air quality management area where air quality objectives are not being achieved. Article 13 then requires a district council to develop an Action Plan for the air quality management area.

PM$_{2.5}$	PM 8-9	(8.06-8.99)	154	6.2
	PM 9-10	(9.0-9.99)	828	33.1
	PM 10-11	(10.0-10.99)	697	27.9
	PM 11-12	(11.0-11.99)	620	24.8
	PM 12-13	(12.0-12.99)	181	7.2
	PM 13-14	(13.0-13.87)	21	0.8
	AQMA 300m	(≤300m)	2030	81.2
	AQMA outside	(≥300m)	35	1.4
	AQMA Inside	NA	436	17.4
Roads Noise	Base	(50-53.99)	1601	64.0
	V. Low	(54-58.99)	540	21.6
	Low	(59-63.99)	172	6.9
	Moderate	(64-68.99)	68	2.7
	High	(69-73.99)	61	2.4
	V. High	(74-78.99)	41	1.6
	Extreme	(>79)	17	0.7
Rail Noise	Base	(50-53.99)	2241	90.6
	Low	(54-58.99)	32	1.3
	Moderate	(59-63.99)	66	2.7
	High	(64-68.99)	78	3.2
	V. High	(>69)	57	2.3
Airport Noise	Base	(50-53.99)	1639	65.5
	Low	(54-58.99)	646	25.8
	Moderate	(59-63.99)	192	7.7
	High	(64-68.99)	24	1.0
Industry Noise	Base	(≤50)	2468	98.7
	High	(>59)	33	1.3

<<<Table III Distance variables frequency sampling>>>

	Noise sources			
Distance Bands	Road	Rail	Airport	Industry
25	113	30	NA	NA
50	104	55	NA	NA
75	127	93	NA	NA
100	189	26	NA	NA
125	218	15	NA	NA
150	220	24	NA	NA
175	115	24	NA	NA
200	157	22	NA	78
225	109	27	NA	NA
250	145	23	NA	NA

>250	1004	2162	NA	NA
400	NA	NA	NA	156
>400	NA	NA	82	2267
1001-1500	NA	NA	159	NA
1501-2000	NA	NA	87	NA
2001-2500	NA	NA	190	NA
>2500	NA	NA	1982	NA

Table IV Variable Descriptions

Variable	Description	Type
Price	Transaction price (£) time adjusted	C
In(Price)	Log of transaction price (£)	C
House Type	Type of property (Transformed to binary e.g. 1 if TER; 0 otherwise)	B
Age	Age of the property (Transformed to binary e.g. 1 if PRE1919 ; 0 otherwise)	B
Size	House size (m^2)	C
Heating type	Type of heating (Transformed to binary e.g. 1 if Oil; 0 otherwise)	B
Build Type	Transformed to binary e.g. 1 if social build; 0 otherwise	B
Garage	Transformed to binary e.g. 1 if GAR; 0 otherwise	B
Air Quality NO_2	Level of Nitrogen dioxide micrograms of contaminant per cubic metre (Transformed to binary for value ranges e.g. 1 if low air quality; 0 otherwise	B
Air Quality $PM_{2.5}$	Level of Particle Matter micrograms of contaminant per cubic metre (Transformed to binary for value ranges e.g. 1 if $PM_{2.5}$ (8.01-9.00); 0 otherwise	B
AQMA	Air Quality Management Area (Binary e.g. 1 if house located inside AQMA; 0 otherwise)	B
Road Noise	Level of road noise measured as the logarithm of the ratio of a given time-mean-square, standard-frequency-weighted sound pressure for a stated time period. (Binary e.g. 1 if Road noise low; 0 otherwise)	B
Rail Noise	Level of rail noise measured as the logarithm of the ratio of a given time-mean-square, standard-frequency-weighted sound pressure for a stated time period (Binary e.g. 1 if Rail noise low; 0 otherwise)	B
Airport Noise	Level of airport noise measured as the logarithm of the ratio of a given time-mean-square, standard-frequency-weighted sound pressure for a stated time period (Binary e.g. 1 if Airport noise low; 0 otherwise)	B
Industrial Noise	Level of industrial noise measured as the logarithm of the ratio of a given time-mean-square, standard-frequency-weighted sound pressure for a stated time period (Binary e.g. 1 if Industrial noise base; 0 otherwise)	B
Road Distance	Distance from nearest main arterial road (Binary e.g. 1 if <25m; 0 otherwise)	B
Rail Distance	Distance from nearest railway line (Binary e.g. 1 if <25m; 0 otherwise)	B
Airport Distance	Distance from nearest city airport (Binary e.g. 1 if >1001-1500m; 0 otherwise)	B
Industry Distance	Distance from nearest industrially zoned area (Binary e.g. 1 if <400m; 0 otherwise)	B

C: Continuous; B: Binary

<<<Table V OLS Linear and Log-Linear Models>>>

	(1)	(2)

	Linear		Log-linear		
	β	*t*	*β*	*t*	*%effect*
(Constant)	64520.655	7.651***	11.208	152.631***	73716.83
AREA	984.173	40.962***	.008	36.788***	0.80%
APP	26783.922	11.888***	.232	11.815***	26.11%
DET	44882.795	20.154***	.349	18.017***	41.76%
SDT	12213.843	9.105***	.165	14.084***	17.94%
PRE1919	-12068.371	-8.082***	-.082	-6.332***	-7.87%
POST1980	4313.548	1.910*	.092	4.663***	9.64%
POSTWAR	-5143.561	-3.402***	.000	.033	0.00%
EARLYMODER	-5168.802	-2.731***	.008	.470	0.80%
ELECHEAT	-1801.579	-.956	-.024	-1.453	-2.37%
GASHEAT	-235.123	-.224	-.004	-.485	-0.40%
SOLIDHEAT	-20.006	-.012	.002	.144	0.20%
SOC	-11022.089	-6.185***	-.138	-8.920***	-12.89%
NOGAR	-1338.239	-1.198	-.018	-1.837*	-1.78%
Air Q Low	-5459.501	-2.477**	-.066	-3.425***	-6.39%
Air Q High	4677.732	1.957**	.050	2.424**	5.13%
Air Q Very High	29829.619	4.988***	.349	6.704***	41.76%
PM8_9	6568.690	2.602***	.061	2.769***	6.29%
PM10_11	-2325.647	-1.243	-.023	-1.419	-2.27%
PM11_12	-11669.558	-4.199***	-.098	-4.061***	-9.34%
PM12_13	-11885.036	-1.452	-.101	-1.982**	-9.67%
PM13_14	-13055.665	-1.386	-.118	-2.434**	-11.13%
AQMA Within300	-773.144	-.192	.013	.372	1.31%
AQMA Inside	2624.339	1.527	.037	2.489**	3.77%
Road Noise V Low	-128.152	-.096	-.012	-1.043	-1.19%
Road Noise Low	2914.370	1.394	.026	1.456	2.63%
Road Noise Moderate	-1833.483	-.621	-.002	-.066	-0.20%
Road Noise High	3667.620	.900	.002	.050	0.20%
Road Noise V High	918.180	.187	.037	.863	3.77%
Road Noise Extreme	1290.596	.204	.008	.151	0.80%
Road_25	-4728.319	-1.285	-.023	-.711	-2.27%
Road_50	-2478.698	-.923	-.021	-.886	-2.08%
Road_75	-2109.971	-.913	-.021	-1.029	-2.08%
Road_100	1617.957	.846	.017	1.025	1.71%
Road_125	-1048.081	-.575	.005	.289	0.50%
Road_150	2384.342	1.316	.017	1.074	1.71%
Road_175	970.000	.423	.004	.204	0.40%
Road_200	-2612.830	-1.313	-.007	-.407	-0.70%
Road_225	7514.066	3.218***	.055	2.685***	5.65%
Road_250	4800.880	2.338**	.037	2.082**	3.77%

Rail_25	915.277	.197	.073	1.795*	7.57%
Rail Noise Low	-27487.45	-2.415***	-0.441	-4.160***	-35.63%
Rail Noise Mod	-5678.95	-0.460	0.004	0.032	0.37%
Rail Noise High	-24811.37	-2.179**	-0.365	-3.445***	-30.58%
Rail Noise V high	19069.76	1.670*	0.151	1.425	16.35%
Rail_50	-11206.596	-3.087***	-.041	-1.302	-4.02%
Rail_75	-5504.543	-1.718*	-.013	-.452	-1.29%
Rail_100	-17789.479	-3.683***	-.103	-2.459**	-9.79%
Rail_125	-12567.617	-1.939**	-.045	-.801	-4.40%
Rail_150	3099.302	.584	.065	1.400	6.72%
Rail_175	-373.185	-.075	.011	.243	1.11%
Rail_200	-7930.388	-1.569	-.103	-2.330**	-9.79%
Rail_225	-7541.898	-1.668	-.036	-.925	-3.54%
Rail_250	-5447.877	-1.121	-.027	-.635	-2.66%
Airport Noise Low	-3105.489	-1.517	-.010	-.557	-1.00%
Airport Noise Mod	-4698.304	-1.221	-.032	-.959	-3.15%
Airport Noise High	-6349.414	-1.024	-.079	-1.454	-7.60%
Airport400_1000	-16552.490	-2.385**	-.056	-.931	-5.45%
Airport1001_1500	-10388.389	-1.807*	-.026	-.527	-2.57%
Airport1501_2000	-9955.022	-2.219**	-.086	-2.196**	-8.24%
Airport2001_2500	-10345.695	-3.125***	-.076	-2.637***	-7.32%
Industry Noise Base	-12765.213	-1.786*	-.149	-2.389**	-13.84%
Industry Distance400	-7160.737	-3.119***	-.084	-4.216***	-8.06%
Industry Distance200	3415.499	.851	.006	.166	0.60%
R^2	0.809		0.815		
Adjusted R^2	0.800		0.807		
AIC	58347.98		57201.67		
F	91.10***		95.09***		
n	2,501		2,501		

NB: Spatial wards available in Appendices. Time variable available on request.
Denotes: ***99% level; **95% level; *90% level

<<<Table VI GWR coefficients>>>

Parameters	min	1st Qu.	Median	3rd Qu.	Max
Intercept	10.04488	10.317	10.50732	10.75813	11.4698
AREA	0.003709	0.006883	0.007629	0.008845	0.0125
APP	0.044103	0.195197	0.302798	0.398363	0.6095
DET	-0.37527	0.287017	0.335969	0.382142	0.6255
SDT	0.006307	0.118544	0.154686	0.194263	0.4962
PRE1919	-0.29011	-0.09524	-0.0422	0.000211	0.0791
POST1980	-0.16995	0.034962	0.088613	0.144219	0.3708

POSTWAR	-0.22547	-0.05829	-0.01578	0.033793	0.1665
EARLYMODER	-0.33133	-0.03715	0.036268	0.087848	0.5864
ELECHEAT	-0.17724	-0.05087	-0.01808	0.01086	0.11
GASHEAT	-0.08838	-0.02672	-0.00578	0.015605	0.066
SOLIDHEAT	-0.13769	-0.01143	0.013233	0.035798	0.1434
SOC	-0.45753	-0.17667	-0.11152	-0.03822	0.1695
NOGAR	-0.12862	-0.0356	-0.01238	0.008318	0.0686
Air Low	-0.51179	-0.1294	-0.05916	0.068024	0.2743
Air High	-0.36426	-0.0184	0.028329	0.094529	0.3003
Air Very High	-0.39895	-0.03821	0.091154	0.210515	0.4235
Part_mat8_9	-0.30017	0.146077	0.366976	0.573741	0.9877
Part_mat9_10	-0.30611	0.073342	0.244157	0.406436	0.6016
Part_mat10_11	-0.4055	0.083145	0.218267	0.409633	0.7065
Part_mat11_12	-0.5988	-0.06218	0.069224	0.236632	0.4633
Part_mat12_13	-0.74736	-0.06276	0.152049	0.310833	1.0128
AQMA_Within300	-0.73802	-0.23896	-0.065	0.085322	0.2262
AQMA Inside	-0.41201	-0.10247	0.031926	0.137125	0.3339
Road Noise V. Low	-0.39784	-0.10161	-0.05768	-0.0047	0.1417
Road Noise Low	-0.34726	-0.13104	-0.04677	0.046925	0.3026
Road Noise Moderate	-0.33628	-0.12076	-0.05448	0.004413	0.2293
Road Noise High	-0.93399	-0.21449	-0.11814	-0.04939	0.1945
Road Noise V. High	-0.17279	-0.01498	0.055416	0.11827	0.3699
Road Noise Extreme	-0.55339	-0.19485	-0.1067	0.069955	0.495
Road_25	-0.1841	-0.08559	-0.04993	-0.01087	0.2707
Road_50	-0.3119	-0.04885	-0.00306	0.03743	0.239
Road_75	-0.3353	-0.07272	-0.02958	0.01605	0.3162
Road_100	-0.1128	-0.03881	-0.00493	0.06042	0.3409
Road_125	-0.1767	-0.05847	-0.01031	0.06016	0.1858
Road_150	-0.0998	-0.01556	0.02136	0.06593	0.2071
Road_175	-0.1526	-0.01055	0.04263	0.08869	0.2883
Road_200	-0.1705	-0.07126	-0.0403	-0.01196	0.1788
Road_225	-0.1429	-0.03221	0.02923	0.1596	0.3939
Road_250	-0.09446	-0.02659	0.01818	0.05744	0.1492
Rail Noise Low	-0.6667	-0.34071	-0.21947	-0.11381	0.1385
Rail Noise Moderate	-3.42566	-0.04185	0.04535	0.153624	8.9443
Rail Noise High	-0.78497	-0.49088	-0.29307	-0.23933	0.423
Rail Noise V. High	-0.28753	0.080428	0.154869	0.235694	0.7482
Rail_25	0.003949	0.1248	0.1808	0.2556	0.4809
Rail_50	-0.3125	-0.03044	0.07784	0.2147	0.5109
Rail_75	-0.1334	-0.01932	0.07497	0.2035	0.3566
Rail_100	-0.206	0.006768	0.07622	0.189	0.3428
Rail_125	-0.2445	0.0732	0.1344	0.2063	0.4515

Rail_150	-0.1155	0.02697	0.1178	0.2083	0.3777
Rail_175	-0.1372	0.04042	0.1331	0.2068	0.4379
Rail_200	-0.2876	-0.1492	-0.08597	-0.00163	0.1592
Rail_225	-0.3425	-0.1442	-0.00627	0.0814	0.1989
Rail_250	-0.2802	-0.01162	0.0412	0.1152	0.229
Airport Noise Low	-0.19238	-0.06323	0.04587	0.172265	0.5697
Airport Noise Mod.	-0.53043	-0.34411	-0.20467	-0.09965	0.2168
Airport Noise High	-0.67079	-0.42741	-0.28136	-0.10115	0.4266
Airport400_1000	-0.2111	-0.1073	-0.0475	0.04688	0.1988
Airport1100_1500	-0.1007	-0.01716	0.0502	0.09886	0.7588
Airport1600_2000	-0.4609	-0.2464	-0.1051	-0.02342	0.0312
Airport2100_2500	-0.3426	-0.2032	-0.125	-0.05381	0.0099
Industry Noise Base	-0.30042	-0.13967	-0.01387	0.089622	0.4612
Industry Distance400	-0.2464	-0.1052	-0.05878	-0.01716	0.0796
Industry Distance200	-0.2371	-0.128	-0.08142	-0.00702	0.1248

	Linear	*Log-linear*
R^2	0.9026	.8993
Adjusted. R^2	0.8553	.8447
AIC	56574.29	-2367.07
AICc	56573.29	-1451.03
RSS	53.24	45.05
n	2,501	2,501

Kernel function: exponential. Adaptive bandwidth: 40 (number of nearest neighbours)
Regression points: the same locations as observations are used.
Distance metric: Great Circle distance metric is used

<<<Table VII Flight Path effect on house prices>>>

	(1) Linear	(2) Log-linear		(3) GWR				
	β	β	%effect	min	1st Qu.	Median	3rd Qu.	Max
Mod. flight noise	-1215.8**	-.040**	-3.95%	-0.3615	-0.1945	-0.1331	-0.0683	0.0413
High flight noise	-3854.2**	-.075**	-7.26%	-0.9453	-0.3511	-0.1426	-0.0195	0.0903
Under flight path	-6560.8**	-.056**	-5.45%	-0.1837	-0.0572	-0.0168	0.0248	0.1344

Denotes: ***99% level; **95% level; *90% level

<<<Table VIII Spatial Lag Models>>>

			Air Pollution Models			Noise Pollution	
	(1) (Base No Lag)	(2) (Base +Lag)	(3) (NO_2)	(4) (PM2.5)	(5) Rail	(6) Airport	(7) Road
C	10.408 (204.587)***	0.1259 (0.967)	2.8883 (5.814)***	6.8997 (6.247)***	1.5883 (4.930)***	0.0142 (0.041)	0.0862 (0.398)
$W_{i,j} = 1/e^{d_{i,j}}$	NA	0.958673 (80.659)***	0.706914 (16.211)***	0.331722 (3.414)***	0.827571 (29.155)***	0.967677 (31.560)***	0.9621 (50.103)***

$W_{exp}P_j * NO_2$	NA	NA	0.017422 (6.439)***	NA	NA	NA	NA
NO_2	NA	NA	-0.19054 (-6.170)***	NA	NA	NA	NA
$W_{exp}P_j * PM2.5\mu g/_{m^3}$	NA	NA	NA	0.064866 (6.812)***	NA	NA	NA
$PM2.5\mu g/_{m^3}$	NA	NA	NA	-0.70096 (-6.478)***	NA	NA	NA
$W_{exp}P_j * Rail$	NA	NA	NA	NA	0.081707 (5.131)***	NA	NA
Rail Noise	NA	NA	NA	NA	-0.9084 (-4.973)***	NA	NA
$W_{exp}P_j * Airport$	NA	NA	NA	NA	NA	-0.0033 (-0.2737)	NA
Airport Noise	NA	NA	NA	NA	NA	0.04471 (0.326)	NA
$W_{exp}P_j * Road$	NA	NA	NA	NA	NA	NA	-0.002 (0.233)
Road Noise	NA	NA	NA	NA	NA	NA	0.02389 (0.234)
AREA	0.01009 (34.729)***	0.003986 (23.380)***	0.003905 (23.431)***	0.003931 (23.758)***	0.004007 (23.735)***	0.003974 (23.299)***	0.00398 (23.342)***
APP	0.366772 (15.078)***	0.051301 (3.835)***	-0.00555 (-0.392)	-0.00617 (-0.447)	0.037728 (2.796)***	0.04626 (3.387)***	0.05144 (3.784)***
TER	-0.10434 (-6.728)***	-0.025474 (-3.101)***	-0.03527 (-4264)***	-0.0378 (-4.617)***	-0.03192 (-3.809)***	-0.02886 (-3.441)***	-0.0255 (-3.110)***
DET	0.204127 (8.315)***	0.034670 (2.650)***	0.048884 (3.767)***	0.058726 (4.497)***	0.03604 (2.777)***	0.033414 (2.542)**	0.0344 (2.629)***
PRE1919	-0.06371 (-2.222)**	-0.065664 (-4.356)***	-0.08027 (-5.421)***	-0.08606 (-5.841)***	-0.06855 (-4.579)***	-0.06753 (-4.472)***	-0.0655 (-4.341)***
INTERWAR	-0.03624 (-1.355)	-0.041892 (-2.978)***	-0.05072 (-3.683)***	-0.05496 (-4.013)***	-0.03979 (-2.854)***	-0.04325 (-3.071)***	-0.0419 (-2.981)***
POSTWAR	-0.03179 (-1.099)	-0.078489 (-5.157)***	-0.07516 (-5.055)***	-0.07323 (-4.956)***	-0.07922 (-5.257)***	-0.07649 (-5.004)***	-0.0785 (-5.154)***
EARLYMODER	-0.00802 (-0.249)	-0.068598 (-4.054)***	-0.06558 (-3.967)***	-0.06552 (-3.990)***	-0.0695 (-4.149)***	-0.06687 (-3.934)***	-0.0685 (-4.051)***
ELECHEAT	0.00069 (0.022)	-0.012883 (-0.794)	-0.01024 (-0.646)	-0.00894 (-0.567)	-0.01371 (-0.854)	-0.01285 (-0.792)	-0.0129 (-0.778)
GASHEAT	-0.01906 (-0.811)	-0.002525 (-0.204)	-0.00191 (-0.157)	-0.00047 (-0.039)	-0.00419 (-0.342)	-0.0023 (-0.185)	-0.0026 (-0.215)
OILHEAT	-0.01857 (-0.858)	-0.002954 (-0.259)	-0.00241 (-0.217)	-0.00062 (-0.056)	-0.0038 (-0.337)	-0.00291 (-0.256)	-0.0029 (-0.258)
PRIV	0.186685 (8.525)***	0.056389 (4.849)***	0.057544 (5.054)***	0.055683 (4.920)***	0.05453 (4.721)***	0.052528 (4.445)***	0.0564 (4.836)***
GAR	0.003206 (0.219)	0.010816 (1.409)	0.012548 (1.673)*	0.012156 (1.632)	0.009612 (1.264)	0.011042 (1.439)	0.0105 (1.378)
R^2	0.5460	0.8744	0.8804	0.8819	0.8771	0.8746	0.8745
Adjusted R^2	0.5436	0.8737	0.8796	0.8812	0.8763	0.8738	0.8736
F-statistic	230.11 ***	1237.26 ***	1143.09 ***	1160.20 ***	1108.03 ***	1083.68 ***	1081.40 ***
AIC	0.297	-0.987	-1.034	-1.047	-1.006	-0.987	-0.986
Log-likelihood	-357.83	1249.87	1310.42	1326.78	1276.18	1251.84	1249.06
Observations	2,501	2,501	2,501	2,501	2,501	2,501	2,501

Denotes: ****p<.001; **p<.05; *p<.10.*