# Two Essays on Convergence of Recycling Rates in England and the Valuation of Landfill Disamenities in Birmingham

by

Yun-Ju Ham

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# Abstract

This thesis is divided into two studies which investigate two separate topics relating to waste management.

The objective of the first study is to test the presence of convergence in recycling rates across local authorities in England over the last decade, 1998-2008. Understanding the distribution of recycling performance across municipalities and its dynamic nature is important for current policy evaluation and future policy decisions. Using various concepts of convergence, a comprehensive analysis of the distribution of recycling rates is provided. Spatial effects are taken into account in the process of convergence since the mechanisms for convergence, such as spillovers of technology or policy ideas, have a geographical dimension. The results indicate the presence of convergence over the whole period in a sense that poor-performing local authorities have the potential to increase recycling activities at a faster rate than initially better-performing authorities. However, with the more aggressive economic instruments in use after 2005, there seem to be two separate convergence clubs which implies convergence within groups but divergence between groups.

The objective of the second study is to investigate public concern over landfill externalities by examining how real and perceived damage from landfill disposal affects the residential property market. Using data on the property sales and landfill sites in the City of Birmingham in 1997, the analysis highlights the presence of long-term impacts of landfill which endure even after site closure by examining external effects from inactive landfill sites as well as active sites. Furthermore, this study deals with a case where properties are simultaneously located near to multiple landfill sites. This issue should not be neglected in the study of a densely populated area like Birmingham. The results of hedonic price regressions reveal strong evidence of landfill impacts reducing property prices. The approach taken here also provides comprehensive estimates of disamenity effects of living near to landfill sites whilst exploring issues like wind direction, nonlinearity of landfill impacts over distance and differential impacts across landfills accepting different types of waste or possessing different age profiles. The results suggest distinctively different features of disamenity from active and historical landfill sites, particularly in their geographical limits.

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# Abbreviations

| | |
|---|---|
| **BMW** | Biodegradable Municipal Waste |
| **AIC** | Akaike Information Criteria |
| **$CH_4$** | Methane |
| **$CO_2$** | Carbon dioxide |
| **CO** | Carbon monoxide |
| **DEFRA** | Department for Environment, Food and Rural affairs |
| **EA** | Environmental Agency |
| **EMU** | Economic and Monetary Union |
| **EPA** | Environmental Protection Agency |
| **EU** | European Union |
| **GDP** | Gross Domestic Product |
| **GHG** | Greenhouse Gas |
| **GIS** | Geographic Information System |
| **GLS** | Generalised Least Squares |
| **GMM** | Generalised Method of Moments |
| **GWR** | Geographically Weighted Regression |
| **IV** | Instrumental Variable |
| **LATS** | Landfill Allowance Trading Scheme |
| **LM** | Lagrange Multiplier |
| **LR** | Likelihood Ratio |
| **ML** | Maximum Likelihood |
| **MSW** | Municipal Solid Waste |
| **MWTP** | Marginal Willingness To Pay |
| **$NO_x$** | Nitrogen oxide |

| | |
|---|---|
| **$NO_2$** | Nitrogen dioxide |
| **NPL** | National Priorities List |
| **OECD** | Orgafnisation of Economic Co-operation and Development |
| **OLS** | Ordinary Least Squares |
| **$SO_2$** | Sulfur dioxide |
| **UK** | United Kingdom |
| **US** | United States |
| **WHO** | World Health Organization |
| **WS** | Waste Strategy |

# Chapter 1

# Introduction

Over the last few decades, the increasing scale of economic activity has led to a rapid growth in the quantity of waste to the level which threatens to overwhelm the assimilative capacity of the environment. Particularly, municipal solid waste has grown at an unprecedented rate, driven by population expansion, rapid urbanisation, rising standards of living and changes in tastes and consumption patterns. For example, total municipal solid waste generation in OECD (Organisation of Economic Co-operation and Development) countries has increased by 58% from 1980 to 2007, reaching to 623 million tonnes. Among non-OECD countries, municipal waste has more than doubled in emerging giants like China and Russia in a shorter period from 1990 to 2007 (OECD, 2010).

With a massive volume of waste accumulating at a fast rate, waste disposal has been a growing problem worldwide. Historically, a majority of municipal solid waste has been buried in landfills. However, most of existing landfill space is running out and it is more difficult to secure new landfill sites due to a continued intensification of the NIMBY (Not in My Backyard) syndrome. Above all, uncontrolled disposal of waste to landfill has resulted in adverse effects on the environment at a global as well as local scale by contaminating air, water and soil quality. Particularly, with an increasing concern over greenhouse gas (GHG) emissions, mainly methane ($CH_4$) gas generated within landfills, sustainable solutions to waste management have become one of the most challenging environmental issues internationally.

To make matters worse, the scale of toxic electronic and electrical waste or e-waste is the fastest growing waste stream in the industrialised world. In Europe, for example, the annual quantity of e-waste is expected to be 12 million tonnes by 2020 and the challenge of growing e-waste is even more serious in the United States (US) (Economist, 2011, 24th, April). Most of this toxic waste stream also ends up in landfills. Even with a well-regulated landfill site, the toxic chemicals of e-waste will be released into the atmosphere and leach into the land over time, contaminating groundwater and thus posing health and environmental risks to local residents. The situation is far worse in developing countries which (sometimes illegally) import a large proportion of e-waste from developed countries to extract precious materials or to recycle parts for further use. [1] Since they lack appropriate infrastructure for recycling and disposal of e-waste, safety concerns are heightened. This illustrates the need to use systematically waste to promote economic activity through material and energy recovery in order to solve the management problem of increasing e-waste, as well as to save expensive and rare raw materials.

Overall, the problems of excessive and toxic waste arise from the failure to take full account of the environmental consequences of waste generated in the process of economic growth and increasing globalisation. The existence of such market failures, in turn feeds back to economic activities and human welfare through the sustainability characteristics of the environment. Such interdependences should be taken into account in the economic analysis of waste management. This will provide a holistic approach to achieve economic efficiency as well as environmental efficiency in waste management. This necessitates government interventions since markets alone will not deliver the efficient level of waste. In particular, the central objective of waste policy is to internalise negative externalities from landfill

[1] The illegal shipment of e-waste to developing countries is continuing despite an international treaty like the Basel Convention on the Control of the Transboundary Movement of Hazardous Waste and Their Disposal adopted in 1989. There has been criticism on the Basel convention regarding the lack of the mandates and financial resource to tackle the problem. Furthermore, a full ban on export of e-waste under the Basel Ban Amendment has yet to enter the force of law.

disposal and to maximise efficient use of resources from waste. The challenge of efficient resource use lies in removing barriers to recycling/reuse and creating incentives for recycled materials and products. To foster the desired level of waste, environmental economics provides a framework in which the optimal amount of waste to landfill is determined at a level which maximises the net social benefit. Then, a cost-benefit analysis will be further conducted to determine the least cost combination of waste disposal options by equating their marginal social cost. This step should precede the introduction of more specific policy instruments in terms of the provision of a particular collection service, regulatory standards and economic instruments such as tax or permits.

The policy applications of such an environmental-economic framework range from national and supranational efforts to localised attempts to deliver sustainable waste management programmes. At a national level, promulgating policies relating to waste management will stimulate or compel local authorities to recycle/reuse and reduce landfill disposal. At a more local level, local governments may develop their own waste programmes. However, for appropriate policy responses to achieve economic and environmental efficiency, policy makers need to know all of the relevant costs of each waste disposal option. For example, the costs of landfill disposal include the costs of environmental impacts as well as operating costs. Economic valuation is essential to place monetary values on the environmental inputs or outputs of each disposal method. It is for example, of particular interest to evaluate the environmental benefits of landfill diversion in monetary terms.

However, these considerations are only one part of motives for policy choice. There are other aspects affecting the choice of policy for integrated waste management. For example, municipal governments need to check for the efficiency of a waste programme in terms of the institutional and social context in addition to issues of economic efficiency. Socio-demographic characteristics may be critical factors contributing to the success and failure in implementation of a waste management scheme. This implies a variation of policy choice in response to local context across local authorities.

In the light of these considerations this thesis focuses in particular on two different, separate but not unrelated topics. The first study is 'Convergence of recycling rates in England', presented in Chapter 2. The second study is 'Valuation of landfill disamenities in Birmingham', presented in Chapter 3. The overall aim and contribution to knowledge of each study are summarised below.

## 1.1 The First Study

The first study analyses the entire distribution of waste management performance across English local authorities and plots its evolution over the last decade. The rationale for this study stems mainly from the following. First, recycling and reuse has become a far more important part of environmental protection activities with evidence of delinking between economic growth and waste generation in a relative sense but not in an absolute sense at least in most industrialised countries (Mazzanti and Zoboli, 2005 and OECD, 2008). In other words, the elasticity of waste generation with respect to economic growth is positive but less than unity. Despite a slower rate of growth for waste when compared to the rate of the growth rate for economic activity in general, most countries have not yet reached the turning point of decreasing waste generation. The threatened increase in the volume of waste in coming decades must be tackled more aggressively through recycling and reuse.

Second, waste policy in the United Kingdom (UK) has seen dramatic changes since the European Union (EU) Landfill Directive in 1999. The Government introduced the Landfill Tax Escalator and the Landfill Allowance Trading Scheme (LATS) in 2005 to encourage local authorities to manage their waste in a more sustainable manner.

Third, there has been a great progress in landfill diversion through recycling/composting in response to more stringent waste policy in the UK. However, this is accompanied by variations in the distribution of recycling rates across local authorities.

Given two different regimes of waste policy before and after 2005, and the observed uneven distribution of recycling participation, this study takes different empirical approaches to evaluate the performance of waste management over the decade by investigating the presence of a long-run tendency towards the equalisation of recycling rates (i.e. convergence). The division of the period of study into before and after 2005 enables us to examine the effects of newly adopted economic instruments. This is the first attempt to test empirically the hypothesis of convergence in recycling rates, which permits us to investigate whether local authorities have made progress towards long-term goals as well as a movement towards a more even distribution of effort.

The choice of convergence approach is based on the following. First of all, it should be noted that previous studies on environmental convergence, largely focused on $CO_2$ emissions are purely empirical, just examining convergence phenomenon itself. The presence of convergence may matter for climate change model or it is important politically as equalised target across countries may be more acceptable internationally.

Secondly, the Green Solow model developed by Brock and Taylor (2010) provides a theoretical approach why we have to expect convergence in pollution. Despite that, the model is actually more related to EKC because emissions convergence is only by product of EKC and income convergence.

Finally and most importantly, the UK has seen a rapid change in waste policy which may promote the presence of convergence. In response to the EU landfill directive, national targets for landfill diversion and recycling rates are set to meet the EU target and local authorities are required to share equal responsibility to achieve that aggregate level of target. The evaluation of relative performance has become more important to monitor progress towards national and local targets. This provides a reason why we expect convergence in waste management performance.

The study begins with the summary of UK waste policy which highlights the development of recent strategies to attain the share of the UK landfill diversion targeted under the EU Landfill Directive. Based on a comprehensive literature review, the study aims to contribute to the two strands of empirical literature on determinants of household recycling rates and environmental convergence. Firstly, previous studies on recycling rates have largely focused on policy variables, particularly unit-based pricing charges as a key determinant of the variation in household recycling participation across regions or municipalities. However, this literature has, by and large, ignored the endogeneity of local policy choices. Instead of directly estimating the impacts of policy choices across local authorities, the analysis of distribution and its evolution in this study provides the historical trends of recycling performance enabling us to evaluate the existing set of national policies. Furthermore current trends in recycling effort can be used to anticipate the future and thus influence the direction of waste policy.

The study contributes to the existing literature on environmental convergence by investigating various concepts of convergence notwithstanding various data constraints. Three different approaches are employed to examine the presence of convergence: sigma ($\sigma$) convergence, beta ($\beta$) convergence and distribution dynamics. While the first two approaches focus on inter-distributional movements in the entire distribution of recycling rates, the latter provides estimates of inter- and intra-distribution mobility. Furthermore, the possible presence of spatial dependence in recycling rates is incorporated into the analysis of sigma and beta convergence.

## 1.2 The Second Study

The second study attempts to evaluate externalities associated with the existence and operation of landfill sites. While there have already been numerous studies looking at landfill disamenities using property market data, crucial features of the relationship between landfill proximity and residential property have been ignored by previous studies: long-term disamenity impacts which persist even after site closure and the presence of more than one site near to individual properties. These features are particularly important in urban residential property markets since urban areas lack space for new landfills while there are only a few operating sites but a large number of closed sites. Therefore, the distinction between active and historical sites is a key issue to be dealt with while incorporating all sites adjacent to the property into the hedonic analysis.

To begin with, the theoretical framework of the hedonic pricing method is briefly outlined and then all relevant empirical studies on property values and landfill disamenities reviewed. One of the contributions of this study is the use of the landfill dataset from Environmental Agency (EA) combined with by far the largest and detailed dataset for a single urban area courtesy of Bateman et al. (2004). This consists of 10,791 property sales that took place in Birmingham in 1997, each with a set of structural, neighbourhood, accessibility and environmental characteristics. Given the literature review and the examination of data on landfill sites, the study identifies several important factors relating to disamenity impacts from landfill sites, such as the type of waste accepted, the number of years operated and the importance of being located downwind of the nearest landfill site in addition to distance to the property. Incorporating all these factors into the hedonic analysis provides a more comprehensive analysis of disamenity effects.

This study develops three different empirical models which emphasise different aspects of landfill disamenities. The first and second models share a common structure, estimating the effect of proximity to the nearest landfill site and various characteristics of the site. However, the first model takes into account only active sites while the second model includes both active and historical sites. Finally, the third model examines a case where residential properties are simultaneously located proximate to multiple landfill sites, regardless of active or historical status. All these models take into account possible nonlinearity of landfill disamenity over distance which implies decaying effects over distance and the presence of a critical distance cut-off beyond which landfill impacts become zero.

The study once more incorporates spatial dependence and market segmentation into the hedonic price regression. The presence of spatial dependence in property values is tested in a global and local sense using commonly encountered tests of spatial autocorrelation. In hedonic regressions, spatial effects are specified using spatial process models. Furthermore, Birmingham housing market is segmented by property construction types. Spatial heterogeneity is also investigated using the locally linear spatial model.

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# Chapter 2

# Convergence of Recycling Rates in England

## 2.1 Introduction

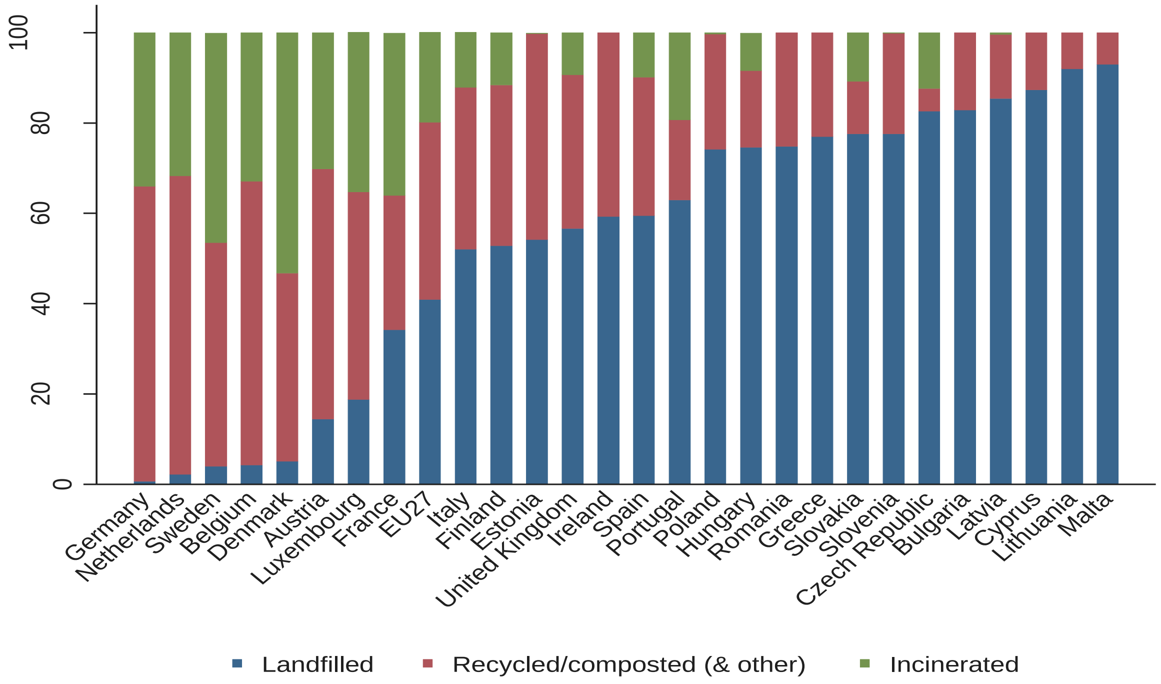
The amount of waste generated has been rapidly increasing in many countries along with the level of economic activity. In recent years, unsustainable patterns of production and consumption have become a major environmental concern as space available for landfill grows scarce and environmental conditions deteriorate. The European Union (EU) has introduced several directives to guide waste management and has set obligations for EU member states to develop better regulations and achieve legal targets for particular aspects of waste management. Despite the pressure from common EU legislation, waste management practices across EU countries have nevertheless shown significant variations. Figure 2.1 summarises municipal waste management across 27 EU countries in 2007. [2] As can be seen, the United Kingdom (UK)'s reliance on landfill is 15% higher than the EU average. Incineration accounts for only a small fraction of waste and recycling/composing performance is also lower than the average rate of EU countries (EU27).

Heavy reliance on landfill disposal is a major contributor to mechane ($CH_4$) emissions, one of the most potent greenhouse gases (GHGs), thereby accelerating climate change. Landfill gas also contains carbon dioxide ($CO_2$) and other toxic pollutants. The leakage of landfill leachate directly affects human health as well as the eco-system through groundwater and soil contamination. Furthermore land sacrificed to landfill generates disamenities to nearby residents, such as odour, noise and dust. Sustainable waste management is important for a

[2] The definition of each disposal category varies across countries. Thus only broad comparison can be made (DEFRA).

range of other purposes such as material and energy security through recovery. While reuse of material supports greater resource efficiency, delivering environmental benefits as well as economic growth, energy from waste through incineration and anaerobic digestion can also contribute a secure renewable energy source helping to meet the UK's demand for energy. [3]

**Figure 2.1: Municipal waste management in the European Union (EU27), 2007**




Source: Eurostat

It was widely recognised that in the UK insufficient action had been taken to reduce environmental hazards from landfill compared to other European countries since the cost of landfill was too low (Martin and Scott, 2003, p.675). Although the UK Government introduced a landfill tax in 1996 in an effort to account for the external costs of landfill, the rate remained low and in fact, landfill disposal takes nearly 80% of total municipal solid waste (MSW) in 1999/2000 (DEFRA, 2004). However, since then the amount of waste

[3] All municipal waste incinerators currently operating in the UK recover energy from waste. Incineration or co-incineration of waste must comply with Waste Incination Directive (2000/76/EC) which sets specific emission limits for the release to atmosphere or water, such as sulfur dioxide ($SO_2$), carbon monoxide (CO), hydrogen chloride (HCI) and particulate (fly ash).

landfilled has started falling faster than at any other time since the EU Landfill Directive (1999/31/EC). Following the Directive, England launched Waste Strategy 2000 and promulgated the Waste and Emission Trading Act 2003 in response to EU Landfill Directive. Over the last decade, the UK has seen a rapid change towards to an incentive-based system to increase landfill diversion and recycling activities.

While the advantage of market-based instruments has been widely advocated as a way to internalise all the externalities in economics, the optimal policy as Palmer and Walls (1997) noted, varies depending on conditions on pollutants type, monitoring costs or availability of information on environmental damage cost. More importantly, one instrument may not be enough to achieve the overall social optimum level of waste or recycling.

This study firstly aims to overview the current UK waste policy and to evaluate policies based on waste management performances over the last decade. In particular, it is of interest to evaluate relative performance across local authorities in the UK as there is greater pressure to meet the EU target for landfill diversion and recycling rates which led the UK to set national target as well as targets for individual local authorities. This study is hoped to guide any future policy changes in waste management and practices.

The statutory provisions undertaken in the last decade have witnessed an overall improvement in waste management in the UK. At the same time however, the distribution of waste management performance across local authorities has been noticeably uneven. Many studies of the determinants of waste generation or recycling participation have sought to explain such variation. Most of these studies focus on policy instruments as the main driving force of household recycling activities. Of these, Abbott et al. (2011) look at household recycling rates across local authorities in the UK and in particular the impact of various features of kerbside collection programmes on recycling rates. However, as Matsumoto

(2011) indicates, the costs and benefits of recycling programmes may vary across municipalities according to the local context and this in turn affects policy choices. Unfortunately, majority of studies do not take into account such endogeneity and fail to econometrically correct for local policy choices determined by observed or unobserved local contexts. [4]

An alternative way to investigate household recycling participation is to analyse the distribution dynamics of recycling. Within the field of environmental economics, most approaches to pollution convergence have been purely empirical with a particular focus on $CO_2$ as its dynamic patterns purportedly have great influence on international agreements concerning the allocation of emissions, as well as on forecasts of global emissions and hence global temperature change. For pollutants in general, environmental convergence has been related to income convergence by the recently developed "Green Solow model" of Brock and Taylor (2010).

With regard to waste management, particularly recycling performances, this convergence approach complements the previous studies on recycling. Moreover, the presence of convergence in waste management is worth examining given that the UK has to meet the EU targets and its local authorities have to share equal share of responsibility to achieve national targets. The choice of convergence approach in particular enables us to address the following research questions: how initially uneven distributions of waste management performance change over time (i.e. is there convergence or divergence), and what implications the dynamic nature of recycling performance has for future policy.

[4] In the literature on the trade-environmental relationship, Ederington and Mineier (2003) and Levinson and Taylor (2008) consider the endogeneity of environmental regulation which correlates with trade flows. Since the cost of complying with environmental regulations significantly increases the costs of domestic products thus reducing competitiveness in the global market, countries may weaken environmental regulation to protect their domestic industry.

The analysis is extended to test the presence of spatial dependence in recycling performance and its evolution over time. The empirical growth literature has pointed to spatial dependence as a significant driver of regional convergence (Rey and Montouri, 1999, p.145). Convergence of recycling rates across local authorities would also be induced through geographical diffusion of ideas, practices and policies through immitation. The literature on political yardstick competition[5] emphasises information dissemination as an important form of cross-municipality interaction in policy mimicking actions. These mechanisms are all more likely to occur among geographically closer authorities, and thus it is important to consider spatial effects as an additional factor to induce convergence in waste management trends across local authorities.

The present study utilises various measures of convergence to investigate the evolution as well as distribution of recycling performance across local authorities in England while taking into account spatial effects. The convergence measures used include sigma ($\sigma$) convergence, beta ($\beta$) convergence and non-parametric analyses for distribution dynamics. While the conventional concepts of convergence consider average or representative behaviour, non-parametric stochastic kernel help to reveal patterns of distributional mobility.

The data cover two time periods: 1998-2003 and 2005-2008. In the first period, the Landfill Directive provides real impetus to UK waste policy and management. In the second period, a set of more aggressive national waste policy are introduced, chiefly higher landfill tax rates and the trading of landfill allowances. The difference between these two periods provides an opportunity to investigate the effects of the more vigorous application of market-based instruments on the observed presence and patterns of convergence.

[5] This is suggested originally by Salmon (1987) as "yardstick competition" in decentralisation and public finance. The effect of political yardstick competition refers to the situation where governments are forced to interact strategically each other in formulating their policies as voters can compare the performance of their politicians with politicians in neighbouring jurisdictions.

Three main results of the current study can be summarised thus. There is strong empirical evidence of catching-up in recycling performance across local authorities over time in both time periods. In addition there is evidence of a high degree of mobility of local authorities, particularly those with low recycling rates, towards the national mean in the first period. On the other hand, the second period is characterised by a pattern of club convergence (i.e. clustering of similar values either below or above the national average) which implies divergence between low and high recycling rates. Finally, spatial dependence in the distribution of recycling rates is highly significant statistically.

The remainder of this study is organised as follows. The next chapter summarises waste policies in the UK. Then I provide an overview of three strands of literature: studies on the determinants of household recycling rates, convergence and spatial effects. In the section containing the empirical analysis, I test for the presence of sigma convergence and unconditional and conditional beta as a measure of global convergence. Next, the analysis of distribution dynamics is conducted using nonparametric methods. Spatial autocorrelation tests are applied to recycling rates and incorporated into subsequent regression analyses. The final section concludes.

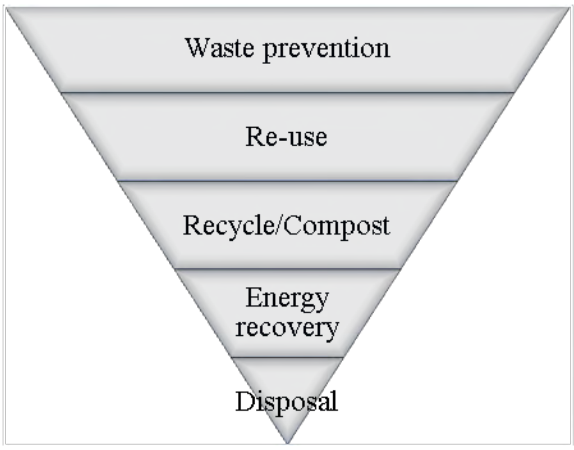
## 2.2 UK Waste Policy

National controls on waste originate from the Control of Pollution Act 1974; the following Environmental Protection Act 1990 was intended to strengthen further pollution controls and ushered in a more integrated scheme for the best practicable environmental option (BPEO). At the EU level, the Framework Directive on Waste (1975/442/EEC of 1975, as last revised by the Directive 2008/98/EC) establishes the overall framework for the management of waste, including definitions and principles.

These policies are centred on the most economically efficient means of collecting and disposing of waste to landfill without placing overly much emphasis on environmental concerns about the increasing quantity of waste. Typically households are only required to pay a fixed fee for the collection service local authorities offered and to put their bin out on the appropriate day.

However, as the public becomes more aware of environmental issues, the mood has changed and policy makers have searched for effective strateigies to manage waste given the principal of 4Rs of reduce, reuse, recycle and recover contained in the waste hierarchy (Figure 2.2) defined in the EU Framework Directive on Waste. In order of desirability, waste prevention is the most preferred option in the waste management hierarchy and landfill disposal is the least preferred option, considered after all other measures have been exhausted. Although energy recovery is more desirable than landfill in the hierarchy, this option remains controversial from an environmental point of view because of the emissions.

**Figure 2.2: The Waste Hierarchy**




Source: DEFRA (2007)

The hierarchy has been useful in generating support for the shift to sustainable waste management. However, the hierarchy should probably best be viewed as providing only flexible guidance rather than a strict set of principles due to its inattention to the issue of economic efficiency. The late 1980s and early 1990s witness new institutional relationships between different agencies such as long-term contracts between local authorities and waste disposal companies.

Undoubtedly the most remarkable shift to sustainable waste management starts with the introduction of the Landfill Tax in 1996. Arguably this is the UK's first environmental tax. Although landfill site operators are responsible for paying the landfill tax, it is passed on to those who send their waste to landfills on top of normal landfill fees. Thus, businesses pay the tax in relation to the waste that they send to landfill whereas the costs related to household wastes are paid by local authorities. The tax is charged according to weight and the rate was initially set at £7 per tonne of active waste and at £2 per tonne of inactive (or inert) waste. The Landfill Tax Credit Scheme (LTCS)[6] was introduced at the same time. This scheme encourages landfill operators to support environmental projects by giving them landfill tax credits obtained through the donation of a certain percentage of landfill tax liabilities to environmental bodies.[7]

Unfortunately, these measures failed to improve recycling performance. This raised concerns about whether the tax rate is set too low to support the desired switch from landfill to alternative waste disposal options. The transformation towards a more sustainable waste management starts with the EU Landfill Directive (1999/31/EC) in 1999. Although the UK already participated in diverse EU directives which focus on treatment operations or specific waste streams in the late 1990s, the Landfill Directive is at the heart of the new transformation (Bulkeley and Gregson, 2009, p.931). The Landfill Directive sets challenging targets for EU member states to reduce the amount of biodegradable municipal waste (BMW)

[6] Projects funded by the Landfill Tax Credit Scheme (LTCS) should conform to one of six objects set in Appendix 2.2.

[7] In 2003, the tax credit is capped at 6 % of landfill tax liability from the initial 30%.

sent to landfill.[8] Those EU member states that fail to meet the targets are to be penalised. The UK's targets are to reduce to 75%, 50% and 35% the total amount of BMW produced in 1995 level by 2010, 2013 and 2020 respectively. In addition to these progressive targets on the landfill disposal of BMW, the directive requires uniform technical standards and sets out the requirements for location, conditioning, management, control, closure and preventive and protective measures for landfills; as well as specifying the characteristics of the waste that may and may not be sent to landfill.[9] Furthermore, the revised EU Waste Framework Directive (2008/98/EC) requires member states to recycle 50% of household waste by 2020, including paper, metal, glass and plastic.

**Table 2.1: Waste Strategy**

| **Target** | **WS 2000** | **WS 2007** | | |
|---|---|---|---|---|
| | 2005 | 2010 | 2015 | 2020 |
| **Total recovery of municipal waste** | 40% | 53% | 67% | 75% |
| **Recycling or composting of household waste** | 25% | 40% | 45% | 50% |

The requirements of the EU Directives are incorporated into various pieces of UK legislation. First of all, the UK Government established the waste management agenda for England and Wales through the Waste Strategy (WS) 2000.[10] This sets the national targets for recycling /composting of household waste and recovery of municipal waste. No recycling or recovery

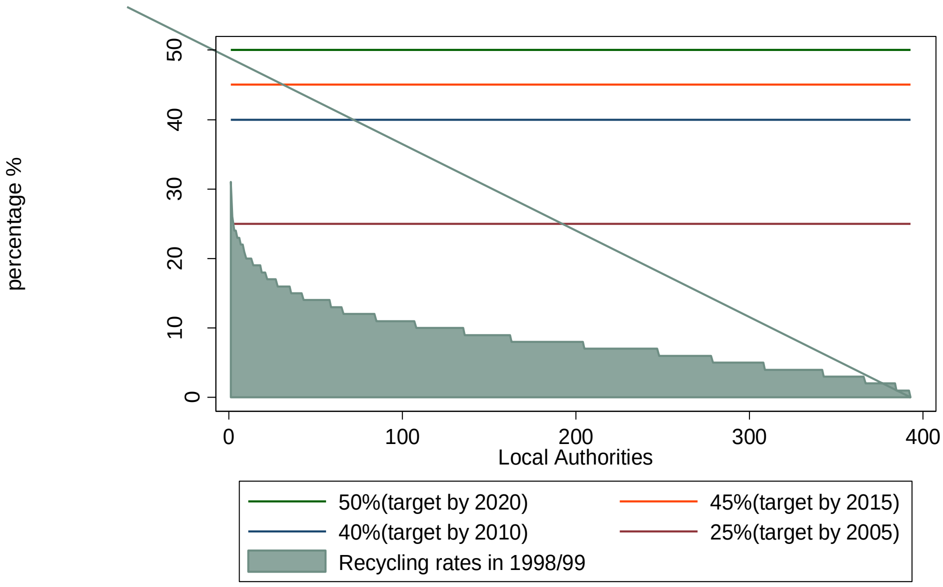
[8] According to the Directive, municipal waste is defined as waste from households as well as other waste which, because of its nature or composition, is similar to waste from households. Biodegradable waste is defined as any waste that is capable of undergoing anaerobic or aerobic decomposition, such as food and garden waste, and paper and paperboard.

[9] The Landfill Regulations introduced some significant changes in the practice of landfill disposal. Particularly, the usual practice of co-disposal of hazardous and non-hazardous waste in the same landfill sites has been banned since 2004. The Regulations also require pre-treatment of waste before it is sent to landfill sites and banned landfill disposal of certain wastes, such as liquid wastes and tyres. Regarding landfill locations, the following considerations should be taken into account; the distances to sensitive receptors, the existence of groundwater, coastal water or nature protection zones; geological or hydro-geological conditions, the risk of flooding, subsidence, or landslides on the site; and the protection of the natural or cultural heritage in the area.

[10] Wales and Northern Ireland have set their own strategies.

targets are set for other waste streams. The latest version of the Strategy in 2007 sets out a wider range of objectives and higher national targets for recycling. Table 2.1 and Figure 2.3 summarise the targets under the WS 2000 and WS 2007. Targets for recycling rates are based on weight. [11]

**Figure 2.3: Local authority recycling performance in 1998/99 and national targets**




Source: DEFRA

Each local authority shares the responsibility of meeting the national targets by achieving their own targets for landfill reduction and material recovery rates based on the performance in waste management in 1998/99. [12] These targets, which may have had a hand in promoting the convergence of performance, were confirmed as statutory targets in 2001. To meet this end, the Government deployed new policy initiatives using both a price-based and quantity-based approach to reduce the amount of waste that is sent to landfill, such as the Landfill Allowance Trading Scheme (LATS) and the Landfill Tax Escalator. Weaver (2005) notes

[11] Weight-based targets for recycling are easy to measure. However, there are concerns on weight-based targets as recycling efforts can be focused on heavier materials such as glass.

[12] For example, for 2003/04 targets, the following criteria are used: 1) local authorities who were recycling under 5% in 1998-99 must recycle over 10%, 2) local authorities recycling between 5-15% in 1998-99 must double their rate and 3) local authorities recycling over 15% in 1998-99 must recycle a third of household waste.

that such responses to the Landfill Directive display the UK's unique interpretation on the EU policy. Particularly, the UK modified the Directive requirements by setting its own targets for recycling which were extended to non-biodegradable materials. The permit system is intended to complement the existing tax regime (although there are doubts about whether it succeeded in this goal). Although the schemes are confined to household waste this has a significant impact on meeting the recycling targets since it contains large quantities of biodegradable waste as well as non-biodegradable wastes.

The following are the detailed description of the schemes introduced in response to domestic as well as international targets for waste management. First of all, the landfill tax system was developed to the Landfill Tax Escalator in 1999, in which the initial rate was raised to £10 per tonne for active waste and further increased by £1, £3 and £8 per year from 1999, 2005 and 2008 respectively.[13] With increasing tax rates and ever less space for landfilling, waste disposal to landfill becomes more expensive and non-landfill waste disposal methods, such as recycling, become a more economical choice for local authorities. The landfill tax revenues have been allocated to improve resource efficiency in business through the Business Resource, Efficiency and Waste (BREW) programme and other schemes for business and local authorities. Of these, the Private Finance Initiative (PFI) and the Waste Implementation Programme (WIP) project support local authorities to invest in non-landfill infrastructure. To minimise waste and to create stable and efficient markets for recycled materials and goods, the Waste and Resources Action Programme (WRAP) has worked on removing barriers to sustainable waste management. In addition, industry and commercial parties have been able to access the latest available technologies and management for reuse and recovery of recyclables through the network provided by Knowledge Transfer Networks (KTNs). Overall,

[13] The rate is given in Appendix 2.1. The rate for inert waste is rather kept constant at a low rate.

the Government has incentivised efforts for waste reduction and landfill diversion through reformed regulations and funding schemes.

The LATS was launched on 1 April 2005. The Waste and Emissions Trading Act (2003) provides the legal framework for the scheme and for the allocation of tradable landfill allowances to each waste disposal authority in England. While the landfill tax is applied to all types of waste generated by business and local authorities, the scheme is aimed at meeting the UK targets for the amount of BMW that can be sent to landfill sites under the Landfill Directive. To this end, the total number of allowances issued reduces each year and allowances are allocated across authorities so that they make the same relative contribution to the targets for each target year (i.e. 2009/2010, 2012/13 and 2019/20), based on their performance in 2001/02. Therefore, if the scheme is effective, local authorities would end up converging on the same rate of recycling. Authorities can borrow, buy, sell or use banked allowances but must not landfill more BMW than their annual allowance. The penalty is £150 per tonne of BMW sent to landfill in excess of allowances held. Appendix 2.3 displays the tonnes of BMW landfill each year and the allocation of allowances, and the trading that occurred.

The incentive to avoid landfilling a tonne of waste is equal to the landfill tax plus the price of LATS allowance per tonne on top of normal gate fees.[14] This cost must equal the marginal cost of alternative waste disposal options. However, there are concerns about the overlap between the instruments. In particular, without environmental justification for the targets set under the Landfill Directive, a quantity-based approach would not result in landfill diversion at an economically and environmentally efficient level. During the first years of the LATS

[14] According to Gate Fee Reports by WRAP (2010), landfill gate fees vary substantially ranging from £11 to £44 with median fee of £22. Gate fees differ depending on spare capacity and local market conditions.

(2005/06-2009/10), the overall performance across authorities far exceeded the quantity targets due to rapidly rising rates of landfill tax (Fullerton et al., 2010, p.495). Therefore, the LATS is not considered a binding constraint for landfill diversion and tax schemes may be sufficient for waste management in the longer term. In addition, the consultation with the leading local authorities and industry bodies reveals that the LATS poses a potential barrier to local authorities collecting business waste. Based on these arguments, the Government announced ending the LATS scheme after 2012/2013.

To sum up, the UK national waste policy is characterised by highly incentivised arrangements for local authorities. They face continuing pressure to divert more waste from landfill as the Government set the targets for landfill reduction and recycling. The Government simply provides the principle to follow when local authorities make operational choices.[15] The Government does not act in a prescriptive manner but provides incentives for meeting landfill reduction and recycling targets through the above economic instruments and a wide range of funding initiatives for business and industries. Given these incentives and the local context, each local authority chooses what for it constitutes the best practice of waste management. Particularly, it is entirely the choice of local authorities as to which waste collection scheme(s) they choose to operate.

Consequently we observe local variations in refuse and recycling collection services, particularly, in terms of the collection frequency (e.g. weekly or fortnightly), the range of material collected (e.g. paper, card, cans, class, plastic bottles, cartons, textiles, shoes and food waste and etc.), the type of collection container provided (e.g. wheeled bins, kerbside

[15] According to Waste Strategy 2000, the Best practicable Environment Option (BPEO) is determined by three criteria: the waste hierarchy, the proximity principle and self-sufficiency. The proximity principle requires waste to be disposed of as close to the place of production as possible. To meet self-sufficiency, wastes should not be exported from the UK and waste authorities should work towards regional self-sufficiency in managing waste (Weaver, 2005, p42).

boxes, sacks) and their sizes. Another important design decision for recycling collection is whether the collection service is commingled or kerb-sort collection. Commingled systems are where materials are collected together and sorted afterwards at a Materials Recovery Facility (MRF). Kerbside sort systems are where materials are sorted by material type at the kerbside into different compartments of a collection vehicle. According to WRAP (2008),[16] kerbside sort was more widely used than the other types of recycling collection systems.

Although there have been some attempts to identify a universally 'best' system, it is difficult to suggest a single design of waste collection which serves all local authorities as the cost-effectiveness of a system may vary according to local circumstances. One scheme may incur more expensive operational costs in some areas due to socio-demographic profiles of their residents and the type of housing. Other important local circumstances may be whether local authority areas are urban or rural and the proximity and available capacity of a suitable MRF as such factors affect the cost structure of running the service. Therefore, recycling policies could be efficient when the characteristics of each area are allowed to determine the nature and extent of their recycling programmes.[17]

As discussed above, in recent years, the UK waste policy at both national and local levels has centred on waste diversion from landfill through capturing recyclables but markedly less effort has gone into waste reduction and reuse. Although it is still more common to use fixed

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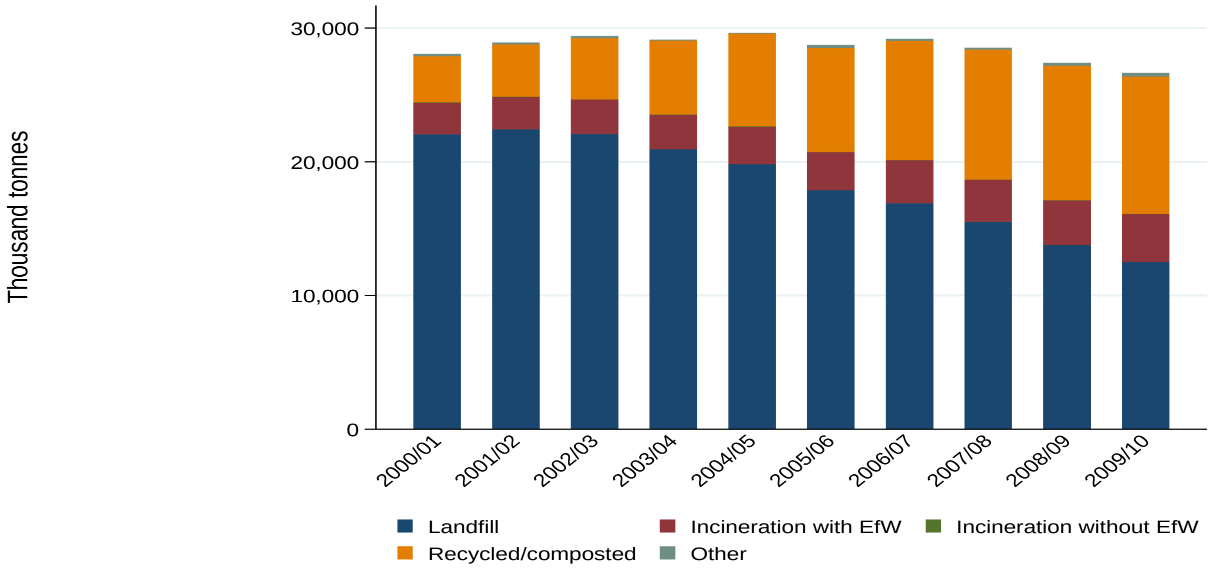
[16] WRAP (2008, p.8) provides a table which summarises key recycling system configuration in England (as at July 2007). See Appendix 2.4 for the summary table from WRAP (2008).

[17] There have been some efforts to compare the cost-effectiveness of different recycling scheme across the UK in an attempt to suggest a better system but they show inconsistent conclusions on a more cost-effective system of recycling collection. For example, according to the report by WYG Environment (2011) based on recycling performance in 2009/2010, co-mingled collection systems in general produced higher yields than kerbside-sort schemes from material sales. On the other hand, the previous reports such as WYG Environment (2010) and WRAP (2008) concluded that kerb-sort collections were in general preferable to co-mingled collections since not only the quality of materials collected from kerbside sort was better but also the cost of co-mingled collections was heavily affected by MRF gate fees. Given varying local conditions, decentralised decision making on recycling policy may allow optimised modes of recycling operation across local authorities and as a result, achieving cost-effectiveness in waste management nationwide.

fees for waste collection from households in the UK, there has been a growing trend in waste policy of introducing variable rate pricing in an attempt to reduce the quantity of waste in other countries. This system is also known as pay as you throw (PAYT) or unit pricing whereby households are charged a rate based on how much waste they produce. There is some evidence from the experience of EU countries and from some parts of the US that unit-based waste collection charges are effective in waste minimisation[18] even though the charges may have only a limited effect in increasing recycling levels.[19] Currently, local authorities in the UK do not provide an incentive to reduce the generation of waste as they use fixed fees which may only depends on the size or value of the house. Furthermore, the UK Government announced that it is actively opposed to any plan to charge households for waste collection as such schemes could encourage illegal dumping and burning waste at home (DEFRA, 2011).

**Figure 2.4: Progress in UK's waste management**




Source: DEFRA

[18] See Callan and Thomas (1997), Podolsky and Spiegel (1998) and Hong and Adams (1999) for evidence of effective user fees for waste disposal in waste minimisation.

[19] See Sterner and Bartelings (1999), Jenkins et al. (2003) and Hage et al. (2009) for evidence of statistically insignificant impacts of the unit-pricing system on recycling participation.

Nevertheless, performance of waste management in recent years shows a need to make more effort to reduce or reuse waste. Figure 2.4 shows changes in waste disposal options chosen in the UK since 2000. As Bulkely and Gregson (2009) argue, the current system may be counter-productive since wastes are merely displaced rather than reduced. While there have been substantial improvement in recycling, there is as yet no great progress in waste prevention. Therefore, there is a need to introduce other complementary schemes to reduce and reuse waste.

## 2.3 Literature Review

The literature review consists of three sections for each separate strand of the literature: the determinants of recycling efforts, convergence and spatial effects. The literature on convergence is subcategorised into providing an overview of various convergence measures and convergence studies in environmental economics. Previous literature for each issue is traced through ECONLIT and references listed in earlier reviews. Literature review on determinants of recycling efforst aims to provide comprehensive overview of the literature by introducing a range of efforts made in the study area and summarising their results.

On the other hand, more focused review of literature is conducted for studies on environmental convergence. All the papers on emission convergence available through the British Library and Libraries of the University of Birmingham are reviewed. For spatial effect, the review briefly introduces the inclusion of spatial externalities in economic growth and convergence literature, which lead us to investigate the presence of spatial autocorrelation and its effect on convergence in recycling rates. Based on this literature review, the next will summarise the implications of previous studies on the current study.

### 2.3.1 Determinants of Recycling Efforts

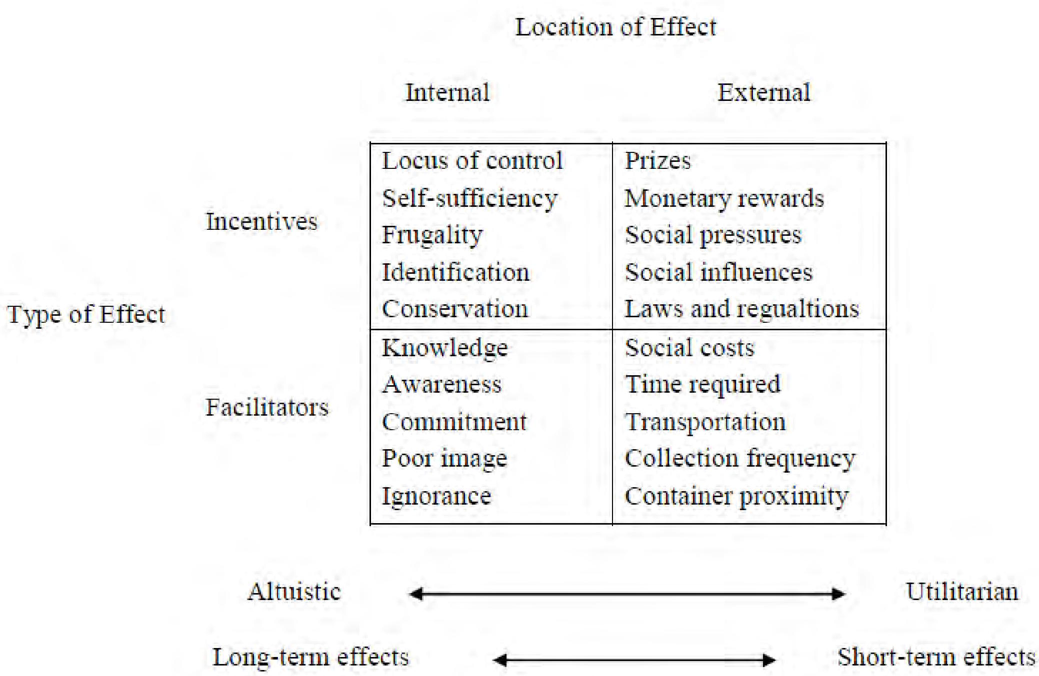
A substantial literature on recycling of household waste has accumulated over the last decade. Theoretically, the importance of household recycling is investigated in Keeler et al. (1971), Plourde (1972), Smith (1972), Lusky (1976) and more recently Huhtala (1999) in dynamic models which specify that solid waste accumulates in the environment as a stock pollutant. In addition, with a particular concern about the scarcity of landfill, dynamic models of optimal waste management have been developed specifying landfill sites as an exhaustible resource and recycling as backstop technology (e.g. Highfill and McAsey, 1997, 2001; Huhtala, 1997).

Another main stream of theoretical studies on waste and recycling is concerned with household waste management behaviour, specifically waste disposal and recycling activities as influenced by economic factors such as income and the price of disposal services, as well as other policy factors like recycling programmes. Wertz (1976) is the earliest paper to develop such a theoretical model. This is followed by further research on specific policy instruments such as Dobbs (1991), Jenkins (1993) and Fullerton and Kinnaman (1995).

Empirically, the determinants of waste management have been widely examined. Some studies use macroeconomic data for total waste or municipal solid waste generation (e.g. Johnstone and Labonne, 2004; Karousakis, 2006; Mazzanti and Zoboli, 2008) while numerous studies examine household waste generation using household surveys or community-level data (e.g. Podolsky and Spiegel, 1998; Linderhof et al., 2001; Dijkgraaf and Gradus, 2004, 2009). While some studies test Environmental Kuznets Curve (EKC) with waste generation, many of these studies are interested in determinants of waste disposal methods as well as waste generation together and even their interaction. Thus the same relevant variables for waste generation are commonly chosen as determinants of recycling performance in terms of economic, socio-demographic and policy aspects. The literature on waste generation is reviewed together with the determinants of recycling performance particularly for policy factors.

Hornik et al. (1995) note that early literature on recycling in the 1970s focuses on the effectiveness of economic incentives and socio-demographic factors to group recyclers and non-recyclers. Economists have worked on this strand of literature and focusing in particular on the role of kerbside recycling and unit pricing in encouraging households to recycle. Later literature from the mid 1980s starts to include social and psychological motivators such as moral and social norms as important drivers of recycling behaviour and analyses the effects of these factors theoretically, and empirically using survey data. Schultz et al. (1995) and Thøgersen (1996) provide reviews of this strand of literature.

**Figure 2.5: Four classes of variables ssed in recycling studies**




Source: Hornik et al. (1995, p.108)

The various determinants of household recycling participation can be categorised along two dimensions as in Hornik et al. (1995): whether variables are identified as motivators or facilitators to recycling behaviour, and whether they are internal or external factors to recyclers. Figure 2.5 summarises these categories.

Hornik et al. (1995) also broadly classify variables as either altruistic or utilitarian. Recycling behaviour is viewed as "Green" altruism when influenced by internal factors such as personal satisfaction or conservation knowledge about recycling. Data on these variables has to be obtained through survey methods. Recycling is labelled utilitarian behaviour when people are more actively involved in recycling because of economic motivation, social influence or convenience. While altruistic variables are believed to have longer-lasting effects than utilitarian variables in promoting changes in recycling behaviour, economists have more focused on the impacts of external factors such as monetary rewards, regulation or other external barriers in terms of time, distance or monetary reward. However, Hornik et al. (1995) find that internal facilitators such as consumer knowledge are the most important factor followed by external incentives such as monetary rewards, social influence and laws.

A distinction between altruistic and utilitarian approaches to recycling behaviour is used to develop two separate strands of theoretical and empirical studies, emphasising the effects of either policy factors or moral norms on recycling behaviour. In addition, socio-demographic variables have been widely investigated as potentially important determinants of recycling participation. In the following, I review the literature on recycling according to these three categories of possible determinants: policy factors, socio-demographical factors and psychological factors. Of a substantial body of literature devoted to trying to understand the recycling behaviour of households, some provide descriptive analyses of survey data (e.g. Perrin and Barton, 2001; Martin et al., 2006; Robinson and Read, 2005) or factor analysis (e.g. Vining and Ebreo, 1990; Vining et al., 1992; Gamba and Oskamp, 1994; Barr, 2007). There are also studies which provide contingent valuation estimates of households' willingness to pay (WTP) for recycling services (e.g. Tiller et al., 1997; Aadland and Caplan, 1999; Bruvoll et al., 2002; Blaine et al., 2005; Bohara et al., 2007). However, I focus on studies which use regression analysis to estimate the impact of various factors on recycling participation.

#### 2.3.1.1 Policy Factors

The economics literature on recycling mostly concerns the effectiveness of policy instruments related to recycling participation and waste minimisation. Policy instruments such as external or utilitarian factors can increase recycling by providing economic incentives or removing barriers to desired behaviour. Regarding economic incentives, the unit-based pricing approach to waste disposal replacing the (widespread) flat fee systems have been theoretically investigated and empirically assessed for its effectiveness in reducing waste as well as for possible waste diversion activities.

As discussed in Kinnaman and Fullerton (1999), the theoretical framework of waste management consists of a utility maximising model of household choice between disposal and recycling and a profit maximising model of producer choice between virgin and recycling inputs.[20] The model includes the choice of economic incentives in the form of tax or subsidy to internalise the full social costs of waste disposal. At the consumption and disposal stage, households face a disposal tax per unit of waste or a subsidy for recycling effort. In production, either a tax on virgin material or a subsidy on recycled materials can be used to achieve source reduction.

[20] See Morris and Holthausen (1994), Fullerton and Kinnaman (1995), Kinnaman and Fullerton (1997, 2000) and Choe and Fraser (1999) for details of the theoretical model developed for household waste management. Except Morris and Holthausen (1994), all considered the problem of illegal dumping and burning as a result of a direct tax on waste disposal.

As argued in Dinan (1993), Palmer and Walls (1997) and Choe and Fraser (1999), the tax (or subsidy) levied on producers has limited effects in correcting the external costs of waste disposal as they do not influence subsequent household behaviour in waste disposal. On the other hand, a direct tax on household waste disposal increases recycling efforts and changes consumption patterns towards products which generate less waste. This will in turn lead to source reduction in production.

Most of theoretical and empirical studies centre on a direct tax on household waste disposal (unit pricing). Empirical studies frequently address the effect of unit pricing systems on the amount of material recycled or residual waste produced. Many of these studies' econometric estimates suggest that unit pricing has a negative effect on waste generation (e.g. Wertz, 1976; Skumatz and Beckinridge, 1990; Jenkins, 1993; Miranda et al., 1994; Fullerton and Kinnaman, 1995, 1996; Kinnaman and Fullerton, 1997, 2000; Podolsky and Spiegel, 1998; Van Houtven and Morris, 1999; Hong, 1999; Linderhof et al., 2001; Dijkgraaf and Gradus, 2004, 2009; Callan and Thomas, 2006) but positive effects on recycling (e.g. Hong et al., 1993; Hong, 1999; Callan and Thomas, 1997, 2006; Dijkgraaf and Gradus, 2004; Ferrara and Missios, 2005; Kipperberg, 2007; Halvorsen, 2008; Hage and Söderholm, 2008). Dijkgraaf and Gradus (2004, 2009) and Hage and Söderholm (2008) furthermore compare different systems of unit pricing, e.g. weight-based fees versus volume-based fees.[21]

At the community or international level, both unit pricing and the impact of landfill tax on waste generation or recycling rates are studied in Bartelings and Linderhof (2006), Karousakis (2006) and Mazzati and Zoboli (2008). Although the results are mixed, Bartelings and Linderhof (2006) find an interesting result in their study which examine the impact of a

[21] While most of unit pricing systems introduced are volume-based fees, it is believed that weight-based fees are more relevant to the external costs of waste disposal. However, the implementation of weight-based fees requires high initial investment cost and thus less frequently used.

change in landfill tax over time in the case of the Netherlands where the landfill tax increased at a significant rate from 13 to 80 euros in 5 years in late 1990s and municipalities partially introduced unit pricing scheme. It is shown that if changes in landfill tax are not incorporated in the charges to waste generators, such a great change in landfill tax seems ineffective.

There are nevertheless instances where user fees are found to be ineffective at increasing recycling levels (e.g. Sterner and Bartelings, 1999; Kinnaman and Fullerton, 2000; Jenkins et al., 2003; Hage et al., 2009; Ferrara and Missios, 2011) and merely increase illegal dumping (e.g. Fullerton and Kinnaman, 1996; Miranda and Aldy, 1998; Dijkgraaf and Gradus, 2004). Jenkins et al. (2003) argue that the ambiguous effects of unit pricing on recycling may be attributed to an adjustment in consumption towards goods that are easy to recycle instead of reducing waste. As a result of such an adjustment, waste generation and the quantity of recycled materials increase but the percentage of recycling may not change. In a review of econometric studies on unit pricing by Kinnaman (2006), it is noted that the price elasticities of the demand for disposal tend to be relatively small even in those studies which obtained statistically significant effects of the scheme.[22] This is because these studies investigated household disposal behaviour in areas where residents already recycled voluntarily under kerbside recycling programmes, and thus the user fee played only a limited role in changing disposal behaviour.

Recycling collection services as measures complimentary to economic incentives are often found to decrease the inconvenience of recycling prior to unit pricing and are expected to play a crucial role in households' voluntary recycling behaviour. According to empirical

[22] The comparison of price elasticities obtained from the existing empirical literature is problematic as their data set examined varies in nature. Some studies used community-level data while others used household level data. Studies also vary as to whether they use time-series, cross-sectional and panel data or whether the dataset is collected within a nation or at the international level.

studies by Reschovsky and Stone (1994) and Hong (1999), the adoption of unit pricing has only limited impacts without subsidiary aggressive recycling programmes. Many empirical studies attempt to identify the key features of individual recycling programmes which have statistically significant impacts on the amount of waste landfilled, as well as recycling participation. The characteristics of recycling schemes include accessibility, frequency of collection and sorting requirements. In general, the literature confirms that the provision of kerbside collection services redoubles recycling efforts (e.g. Derksen and Gartrell, 1993; Callan and Thomas, 1997; Jenkins et al., 2003; Kinnaman, 2005; Halverson, 2008). In addition, the provision of a more frequent collection service is an important factor as residents may be relieved of the burden of storing recycled materials (e.g. Duggal et al., 1991; Jenkins et al., 2003; Judge and Becker, 1993; Ferrara and Missios, 2005). Judge and Becker (1993) find that less strict requirements regarding sorting, such as permitting commingled recyclables, increases household recycling participation rates.

Most recently, Ferrara and Missios (2011) compare four different recycling programmes which include not only kerbside collection services but also drop off services, refundable deposits and bring back with no refund systems. While theoretical studies on optimal waste policy widely advocate the use of deposit-refund policies to reduce illicit burning and dumping (e.g. Dinan, 1993; Dobbs, 1991; Fullerton and Kinnaman, 1995; Palmer et al., 1997; Palmer and Walls, 1997), there is little empirical evidence supporting such a policy. The results of Ferrara and Missios (2011) show that kerbside collection induces higher recycling participation among residents as it is a more convenient system compared to others. Mandatory recycling and a less frequent collection service for residual waste also intensify household recycling efforts.

While a household-level survey dataset is utilised in Ferrara and Missios (2011), Abbott et al.

(2011) compare recycling rates across the UK at the local authority level describing the different methods of kerbside recycling collection in terms of the size of containers and frequency of collection. The results show that wheeled bin methods increases dry recycling performance compared to kerbside boxes which tend to be stored indoor. Green waste collection improves with an increase in frequency whilst dry recycling rates are not affected by how often recyclables are collected.

While most of the existing literature treats policy variables as exogenous, studies like Hong (1999), Kinnaman and Fullerton (2000), Kinnaman (2005), Callan and Thomas (2006), Dijkgaar and Gradus (2009) and Allers and Hoeben (2010) argue that a variation in local waste policies is not independent of the local context and policies are endogenous. For example, municipalities which generate a large quantity of waste may have more pressure to introduce unit pricing. Differences in economic and socio-demographic factors may also explain the variation in local waste management decisions. Therefore studies using community-level data need to correct for the endogeneity of policy instruments often achieved by means of instrumental variables (IVs).

Hong (1999) and Callan and Thomas (2006) specify a two-equation model for the quantity of waste disposal and recycling as determined by policy factors including user fees and /or the frequency of recycling and disposal collection services. These policy variables are assumed to be endogenous. Their work reveals an important interaction between disposal and recycling decisions, and further allows a decomposition of the effects of unit pricing on the quantity of residual waste into a direct and indirect element. Indirect effects of unit pricing come from increased recycling activities to reduce the cost of waste disposal.

Kinnaman and Fullerton (2000) estimate a model for choice of user fees and kerbside recycling programme separately across municipalities and then use the predicted values of these policy factors as determinants of waste disposal and recycling. Their results indicate that prior studies based on the exogeneity of policy variables may substantially underestimate households' responsiveness to unit pricing and/or kerbside recycling programmes.

Kinnaman (2005) models the municipal decision to adopt a kerbside collection programme which is simultaneously determined along with the recycling activities of households. While Kinnaman and Fullerton (2000) use various socio-demographic variables as determinants of policy choices across municipalities, Kinnaman (2005) assumes the adoption of the programme is determined partly by the recycling activities of households as well as the cost of operating the programme. Household recycling activities are determined by socio-demographic factors, environmental preferences and the provision of the collection programme.

Dijkgaar and Gradus (2009) include an extra variable to distinguish those municipalities which introduce unit pricing earlier than others. This is to correct for endogeneity or the "environmental activism effect" which reflects a tendency that better-performing municipalities in environmental management are likely to introduce pro-environmental policies earlier than others. Therefore, a statistically significant effect of unit pricing on waste disposal or recycling, if found, can be largely attributed to different levels of environmental activism across municipalities, and ignoring this will lead to overestimates of the price effects.

Allers and Hoeben (2010) assess the endogenity of the user fee across Dutch municipalities by using the spatio-temporally lagged value as an instrument. In other words, it is assumed that the adoption of user fees is determined by the average user fee in neighbouring municipalities in the previous time period. Such a specification is reasonable since the data display some level of spatial dependence in waste policies. That is, municipalities characterised by a positive user fee are geographically clustered as policy interactions between neighbouring jurisdictions generate mutually reinforcing positive impacts. However, spatial effects can also be negative when there is an influx of waste from high-price jurisdictions to low-price jurisdictions. Nonetheless, the results show the dominant effects of positive spillovers which encourage neighbours to introduce user fee schemes.

Callan and Thomas (1999) and Matsumoto (2011) focus only on the determinants of unit pricing and/or recycling programmes adopted across municipalities. Matsumoto (2011) analyses kerbside recycling programmes adopted across Japanese municipalities which vary considerably in terms of the number of waste separation categories and the frequency of plastic bottle and container collection. The author believes that the choice of recycling programme should fit the demographically-determined needs and preferences of participants.

#### 2.3.1.2 Socio-demographic Variables

Many countries, even with direct charges on waste disposal, rely largely on voluntary recycling programmes to achieve their recycling goals. Voluntary recycling programmes require a significant amount of personal time, space and sorting efforts. Such costs can considerably vary with the characteristics of local residents. Most empirical studies include various socio-demographic variables as proxies for personal costs of recycling activities. In addition to affluence, the most commonly utilised variables include educational level, gender, age, ethnicity, employment status and family composition. Although results vary somewhat across studies, the hypotheses and general findings regarding the effects of key socio-economic variables can be summarised as follows.

The relationship between income and recycling participation is ambiguous. Higher income households have higher consumption, generating more waste. One can argue that more rubbish will potentially require greater efforts to recycle and thus increase the quantity of materials recycled (e.g. Duggal et al., 1991) but decrease the proportion of waste recycled (e.g. Sidique et al., 2010a). A positive relationship is empirically supported by Callan and Thomas (1997), Hong and Adams (1999), Dijkgraaf and Gradus (2009), Ekere et al. (2009) and Sidique et al., (2010b) but these studies vary in their choice of recycling variable, e.g. the quantity of recycling, recycling rates, the number of visits to recycling centres or a probability variable whether households separate waste. Kinnaman (2005) includes a quadratic term of income and finds that income increases recycling rates at a diminishing rate.

Equally however, a negative effect of income on recycling might be expected if the opportunity cost of recycling efforts increases with higher income and a higher value of leisure. To test this hypothesis, studies like Hong (1999) and Halvorsen (2008) include a direct measure of the opportunity cost of time for recycling activities finding negative impacts. Their measures of time are obtained either from the value of mean willingness to pay for leaving household recycling to others or from the female's wage corrected using Heckman's (1974) method.

Hage and Söderholm (2008, p.1726) also note that income increases the demand for environmental improvements but its elasticity is less than one as found in Kristöm and Riera (1996) and Hökby and Söderqvist (2003). In other words, high income households do not necessarily allocate more of their resources than low income households for improvement in environmental quality.

Saltzman et al. (1993), on the other hand, argue that the impact of income varies across recyclable materials, particularly newspaper and glass. As the level of income rises, the recycling rate of newspaper is expected to increase with a change towards pro-environmental behaviours. Unlike newspaper, glass can be substituted with other materials and richer households can buy non-glass materials to avoid spending time and effort recycling glass. Their empirical results, as well as those of Jenkins et al. (2003), support this idea as the estimates of income for newspapers are statistically significant and positive but insignificant for glass. There are a few empirical findings which show no statistically significant effect of income at all (e.g. Sterner and Barterlings, 1999; Dijkgraaf and Gradus, 2004; Callan and Thomas, 2006; Kipperberg, 2007; Hage and Söderholm, 2008; Hage et al., 2009; Sidique et al., 2010a).

High educational levels are expected to stimulate environmental awareness and thus to encourage recycling participation. Many papers find education as one of key determinants of pro-environmental behaviour (e.g. Duggal et al., 1991; Hong et al., 1993; Reschovsky and Stone, 1994; Jakus et al., 1997; Callan and Thomas, 1997; Hong, 1999; Kinnaman and Fullerton, 2000; Sidique et al., 2010a; Ferrara and Missios, 2011). While some studies find statistically insignificant effects, no literature demonstrates a negative effect of education except Hage and Söderholm (2008).

After retirement people may recycle more as they have lower opportunity costs of time and effort spent on recycling activties. Sidique et al. (2010a) note that older people also have higher preferences for compliance with social norms and thus are more likely to participate in pro-environmental activities like recycling. This is supported by Derksen and Gartrell (1993), Jakus et al. (1996, 1997), Sterner and Barterlings (1999), Jenkins et al. (2003), Nixon and Saphores (2009), Sidique et al. (2010a, 2010b) and Ferrara and Missios (2011). Furthermore, Sterner and Barterlings (1999) find that the effect of age depends on what type of material is considered. Older people sort better if materials are refundables while younger people are better at recycling newspaper and hazardous waste.

Using community level data, socio-demographic variables are usually specified as the average value or the share of population, such as mean income per capita, median age, unemployment rate, and the percentage of college graduates. By contrast the use of household-level survey data frequently lacks individual data on the actual quantity or rate of recycling and waste disposal.[23] However, household level data provide more scope to explore the variation in household characteristics and thus include variables like homeownership, household size, marital status, gender, the number of children and structural characteristics of house and etc. A summary of the results obtained from household-level studies can be found in Matsumoto (2011).

Along with household characteristics population density has often been included in empirical analyses. A negative association between recycling participation and population density is, in general, expected for two reasons. Firstly, densely populated areas often have a problem of high congestion and thus have low levels of car ownership. Without a kerbside collection scheme, this will discourage people to use drop-off recycling programmes. Secondly, a large proportion of residents in densely populated areas live in multi-story dwellings which make it difficult to organise a kerbside collection scheme. Even with a kerbside collection scheme, a low recycling rates are expected since residences of such buildings are typically smaller than single-family dwellings and thus do not have enough space to store recyclable materials until they are collected. These effects can be captured by using a variable describing housing type, e.g. single-family dwelling or multi-family dwelling (e.g. Derksen and Gartrell, 1993; Oskamp et al., 1991; Jenkins et al., 2003). Despite this many studies find statistically

[23] Most of household-level studies rely on self-reported recycling behaviour and commonly use latent variables for recycling participation, which distinguish between recyclers and non-recyclers or rely on the ranges of recycling efforts, captured by integers, for example, 1 to 5 for approximately 0%, 25%, 50%, 75% and 100% of recycling as in Ferrara and Missios (2011) or the frequency of a household participation in kerbside recycling or drop-off recycling programmes. Survey-based household data have several drawbacks. Firstly, the survey sample is likely to be biased towards those who are more motivated and involved in recycling activites and hence fail to represent the whole group (i.e., self-selection problems). Another limitation of survey data is that the public's self-declared participation rates for recycling are likely to be exaggerated (Robinson and Read, 2005, p.81). Moreover, it is difficult to examine recycling behaviours for a long period of time, and most of survey studies are bound to be a case study, which analyse one or only a few municipalities. This will result in a fallacy to generalise a local-specific outcome to the whole story of recycling activity. On the other hand, community level studies usually include variables for which data happen to be available and not all relevant characteristics of local communities are estimated in econometric models. When omitted variables are correlated with included independent variables, the estimates of OLS regression are generally biased and inconsistent.

insignificant effects of population density. Sidique et al. (2010a), on the other hand, argue that recycling participation is higher in high-density cities since these big cities have more advantageous conditions when it comes to establishing the infrastructure for convenient recycling programmes and education on recycling activities.

Instead of a linear relationship between density and recycling, Kinnaman and Fullerton (2000), Callan and Thomas (2006) and Dijkgraaf and Gradus (2009) employ a quadratic specification. They assume that there is a higher probability of illegal dumping in very low- and very high-density communities. In very high-density cities, residents may have less social pressure to recycle, and it is easy to dump waste in commercial dumpsters. On the other hand, residents in sparsely populated areas may dump waste in woods or remote spots. Therefore, some studies employ a dummy to distinguish between big city and village in addition to population density. The results on the quadratic term of density are mixed across studies whilst big city or village dummies are often found to be statistically significant with a negative sign.

The negative effect of big cities may be further explained from the perspective of the operating costs of collection schemes in Hage and Söderholm (2008). The cost of recycling schemes consists of two components: transport and land costs. Because of expensive land within the centre of big cities, material recovery companies may be located outside the city and may incur high transport costs. Small cities by contrast can lower transport costs since these companies can be located within the centre where the local authorities can offer favourable charges for land they possess. Thus, the cost of land dominates the total cost of schemes for small cities. Even if the material companies are located outside the centre, the distance from households will not be a concern to small cities.

### 2.3.1.3 Attitudes and Motives

In most economic studies of recycling, the cost of recycling activities at the individual level are usually related only to lost leisure time and savings in waste disposal costs through the reduction of waste. Based on this theoretical framework, the aim of most empirical literature is to analyse how and to what extent policy factors affect household recycling by changing time and monetary costs of the activity. In addition, various socio-demographic factors are included as proxies for private costs of recycling. Such analyses can however, provide only partial explanations for observed behaviour.

To better explain observed behaviour, the economic-psychological literature includes subjective characteristics of individual households in promoting environmentally conscious behaviour. For example, the determinants of recycling behaviour are investigated by linking intention and environmental behaviour based on the theory of planned behaviour[24] in which attitude toward the behaviour, moral norm and perceived behaviour control form a behavioural intention (e.g. Boldero, 1995; Taylor and Todd, 1995; Chan, 1998; Davies et al., 2002; Tonglet et al., 2004). Barr et al. (2001, 2003) categorise a wide range of the possible determinants of recycling behaviour into three: environmental values, situational variables and psychological variables. Situational variables include policy factors and socio-demographic variables. Environmental values represent an individual's value orientation or a general world-view on the environment.

People may possess general environmental concerns as well as attitudes regarding specific environmental issues such as waste disposal and recycling. Psychological factors may come into play including personality, moral motives and perceptions concerning behaviour. For

[24] See Ajzen (1991) for the review of the theory of planned behaviour.

example, environmentally-friendly households may have substantially lower personal "costs" or less disutility from recycling and thus are more likely to recycle. Some individuals may even experience positive feelings from their own recycling activities as they derive moral satisfaction or warm-glow from contributing to the environmental upkeep.

Moral motivation is included within the theoretical framework of utility maximisation in Brekke et al. (2003) and Bruvoll and Nyborg (2004). Based on this line of literature, Halvorsen (2008) and Hage et al. (2009) develop a theoretical framework in which norms affect the utility of households and thus their recycling efforts. For example, Hage et al. (2009) present a model of a norm-motivated recycler in which individuals derive utility from a positive self-image which depends on the perception of moral responsibilities for recycling, individuals' belief about the magnitude of negative external effects from waste disposal as well as positive external effects from their own recycling efforts and the perceived average recycling efforts of all other individuals.

A large number of studies estimate the impact of attitudes and motives in their econometric models, all necessarily based on survey data at the household level. Econometric studies using community-level data have limitations in specifying such aspects of individual households' recycling activities although it may be possible to include the general attitudinal characteristics of a community. For example, Hage and Söderholm (2008) use two proxies to take account general attitudes and concerns about environmental issues in their analysis of municipality-level recycling data from Sweden; a dummy which takes the value unity if the Green Party represents the municipality and the share of votes for the Green Party in the central Government. The results point to a statistically significant and positive effect of votes for the Green party. Kinnaman (2005) also specifies environmental preference by means of the average environmental voting record of a state's congressional representatives and found it to have a statistically significant and positive effect on household recycling activities.

In studies employing household-level survey data, commonly estimated subjective characteristics are environmental concerns and awareness about general environmental issues (including waste), moral norms (i.e. the individual's own level of responsibility), social norms (i.e. shared expectations within society), legal norms (i.e. expectations from authorities and politicians). According to the meta-analysis by Hornik et al. (1995), there is a strong relationship between social norms and recycling participation. The impact of social norms is often captured through variables describing the recycling activities of one's friends, neighbours and other influential people (e.g. Oskamp et al., 1991; Jakus et al., 1996; Hage et al., 2009; Brekk et al., 2010; Sidique et al., 2010b). Chan (1998) includes exposure to media (print, television and radio) as an important source of social pressure but found it to be only weakly correlated with actual recycling behaviour. Nixon and Saphores (2009) separately specify each media source in the regression but find that face to face communication and the influence of peers or family are the most effective in motivating recycling participation (although print media is also a statistically significant factor).

Regarding attitudes towards recycling activities and perception of the importance of individuals' recycling activities,[25] there exists evidence of statistically significant effects found in Oskamp et al. (1991), Van Houtven and Morris (1999), Ekere et al., (2009), Hage et al., (2009) and Brekk et al. (2010). However, as Chan (1998) notes, attitudes and norms may be a good predictor of behavioural intention but not actual behaviour.

Theoretically, Guagnano et al. (1995) and Ölander and Thøgersen (2005) show an interaction

[25] Respondents are asked closed ended questions with a fixed set of responses e.g. yes-no reports or 4-5 points scales from strongly agree to strongly disagree. For example, in Hage et al. (2009) and Brekke et al. (2010), the perception about the personal responsibility for recycling is measured by their extent of agreement with the statement "I feel a responsibility or a moral obligation to recycle".

between moral attitudes and external policy facilitators, such as the existence of a recycling programme. Derksen and Gartrell (1993) estimate the interaction between the convenience of collection services and social norms and find a statistically significant and positive relationship, which underscores the importance of understanding psychological factors to identify conditions under which policy instruments can steer recycling behaviour. Hage et al. (2009) also argue that the extent to which moral attitudes impact on recycling participation may depend on the accessibility and convenience of recycling schemes but their estimate of the interaction between social norms and property-close collection in multi-family dwellings is not statistically significant.

### 2.3.2 Convergence

In recent years, the concept of convergence has attracted much attention in environmental economics chiefly as a means to understand better the geographical distribution of GHG emissions across countries. The existence of convergence on per capita emission carries significant implications for the international effort directed towards mitigating climate change. This has prompted a wave of studies testing for the presence of convergence employing a range of different concepts and techniques. Four major approaches can be identified in emission-convergence literature: beta convergence, sigma convergence, stochastic convergence, and distributional analysis. In the next section each approach to investigating the presence of convergence in emissions is briefly summarised followed by a review of the existing empirical evidence on the convergence process of emission levels.

#### 2.3.2.1 The Concepts of Convergence

The concept of convergence and divergence has been extensively discussed in the growth literature. The theoretical justification for economic convergence stems from the Solow (1956) neoclassical model for international economic convergence. Known as the beta convergence approach (Baumol, 1986) it predicts a negative relationship between the initial income level and the growth rate which arises from the key assumption of diminishing returns to capital. The economic growth of high income countries will be slower compared to that of low income countries since the economy experiences diminishing marginal productivity of capital with any increase in the capital-labour ratio.

Brock and Taylor (2010) amend the Solow model to incorporate technological progress in pollution abatement. The so called Green Solow model suggests that this addition to the neoclassical model coupled to diminishing returns is the fundamental force emission convergence (see Appendix 2.6). Just as in the cross-sectional models of economic convergence specified by Baumol (1986) and Barro and Sala-i-Martin (1992), the empirical model for emissions convergence tests for a negative relationship between the growth rate of emissions per capita and the initial level of emissions per capita. The stylised equation estimated is:

$$\frac{1}{T}\ln(E_{iT}/E_{i0}) = \alpha + \beta \ln E_{i0} + \gamma Z_i + \varepsilon_i \qquad \textbf{(2.1)}$$

where the dependent variable is the average growth rate of per capita emissions for country $i$ over the period, $T$ is the number of periods, $\alpha$ is a constant term, $\ln E_{i0}$ is the log of initial per capita emissions in country $i$, and $\varepsilon_i$ is an independent and identically distributed error term with zero mean and finite variance. $\beta$ is a parameter testing the null hypothesis of no convergence or divergence, from which one can derive the speed of convergence $\lambda$ given by the formula (Barro and Sala-i-Martin, 1992, p.230):[26]

[26] The transitional dynamics of income is quantified by the log-linearised approximation to the neoclassical growth model with a Cobb-Douglas technology (Barro and Sala-i-Martin, 1992, p.225):

$$\log[\hat{y}(t)] = \log[\hat{y}(0)] \cdot e^{-\lambda t} + \log(\hat{y}^*) \cdot (1 - e^{-\lambda t})$$

$$\lambda = -[(1/T)\ln(T\beta + 1)] \qquad \textbf{(2.2)}$$

The speed of convergence measures how fast cross-sectional observations converge towards the steady state each year. The parameter $\gamma$ in the equation (2.1) tests the null of unconditional convergence. To test for conditional convergence, a vector of country-specific factors, $Z_{i,}$ is included. As in the Solow growth model, Brock and Taylor's (2010) model implies that per capita emissions will converge across countries or regions given similar characteristics in terms of population growth, savings, depreciation and technology. Thus, $Z$ includes factors like the investment to gross domestic product (GDP) ratio and population growth. On the other hand, other empirical studies on beta convergence often selected variables for $Z$ based on the review of the EKC literature.

In any study of income convergence, evidence of beta convergence has important implications for income distribution across countries and thus equality issues. It also provides parameter estimates for the determination of patterns of long-run growth, as emphasised in neoclassical growth theory. Beta convergence has been widely investigated in the empirical growth literature. However, Baumol (1986, p.1076) warns of a problem in including the initial status as a regressor due to its use in constructing the dependent variable. Moreover, when beta convergence holds, the rate of convergence is frequently taken as being identical across countries. A number of criticisms of the cross-sectional regression approach of beta

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where $\hat{y}$ is the quantity of output per unit of effective labour, $\hat{y}*$ is its steady state value and λ governs the speed of adjustment to the steady state. The equation implies that the average growth rate between time 0 and $T$ is given by:

$$(1/T)\log[y(T)/y(0)] = x - [(1-e^{-\lambda T})/T]\cdot\log[y(0)] + [(1-e^{-\lambda T})/T]\log(\hat{y}*)$$

The coefficient on $\log[\hat{y}(0)]$ is $-[(1-e^{-\lambda T})/T]$ and λ is estimated nonlinearly. Alternatively the estimated coefficient $\beta$ on $\log[\hat{y}(0)]$ from a linear regression may have a relationship with λ such that $\lambda = -[(1/T)\ln(T\beta+1)]$. The time $t$ for which $\log[\hat{y}(t)]$ is halfway between $\log[\hat{y}(0)]$ and $\log(\hat{y}*)$ satisfies the condition $e^{-\lambda * t} = 1/2$. The half-life is therefore log (2)/ λ*=0.69/ λ*, the time that it takes for half the initial gap to be eliminated.

convergence can also be found in Friedman (1992), Quah (1993a) and Evans and Karras (1996). Therefore, other approaches to convergence analysis have been widely proposed to investigate the dynamics of cross-section distributions of per capita emissions.

The second concept of convergence is related to a declining dispersion parameter for per capita emissions over time. This is known as sigma convergence. With the assumption of log-normally distributed emissions per capita, the cross-sectional dispersion is conventionally measured by the variance (VAR) or standard deviation (SD) of emissions across countries or regions, defined as:

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(\ln E_i - \ln \overline{E})^2}{n}} = \sqrt{VAR} \qquad \textbf{(2.3)}$$

where $n$ is the number of observations, $\ln E_i$ is the log of emissions of country $i$, and $\ln \overline{E}$ is the mean or expected value of emissions. Barro and Sala-i-Martin (2004, p.462) show that the presence of beta convergence theoretically tends to reduce the dispersion of per capita income. However, it does not necessarily generate sigma convergence when there are strong asymmetric shocks which increase the cross-sectional dispersion. Therefore, sigma convergence is a stronger form of assessing the presence of convergence than beta convergence. In order to understand the dispersion in the context of the mean of the data, the coefficient of variation (CV)[27] has also been commonly used as a normalised measure of dispersion.

However, sigma convergence shows only a time trend of cross-sectional dispersion and as Quah (1996, p.1364) points out, neither beta nor sigma convergence yields any kind of

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[27] The coefficient of variation (CV) is defined as the ratio of the standard deviation (SD) to the mean $\overline{E}$ : $CV = SD/\overline{E}$ .

information about the intra-distribution mobility. In other words, these statistics describe only the average pattern of behaviour and fail to provide a picture of how an entire distribution evolves. For example, Quah (1997) shows a situation of emerging twin peaks (i.e. polarisation) or even a multiple peaks (i.e. stratification) in the distribution of income over time. Such behaviour cannot be captured in the beta and sigma convergence approach.

In this respect, the third approach to convergence attempts to understand the dynamics of the entire cross-sectional distributions using nonparametric methods. Such an approach of distributional analysis goes back to the work of Quah (1993a, 1993b, 1996, 1997). Firstly, kernel-smoothed estimates for each year are plotted. Such density estimates enable us to investigate the properties of a given dataset in terms of skewness and multimodality. The kernel estimator for the density function at point $x$ is given by:

$$\hat{f}(x,h) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right) \qquad \textbf{(2.4)}$$

where $n$ is the number of observations and $h$ is the bandwidth, also called the smoothing parameter. The bandwidth controls the smoothness or roughness of a density estimate. The density function is evaluated at each of the $n$ different observations denoted by $x_i$. In emission-convergence literature, $x_i$ is either the log of emissions per capita, $lnE_i$ or relative emissions per capita to the world average, $RE_i = ln(E_i/\bar{E})$. $K(\cdot)$ is a univariate kernel function which is usually chosen to be unimodal and symmetric about zero. The function sums the contribution from each individual point to the overall estimate and thus the influence of each observation is spread about their neighbours. The Epanechnikov kernel[28] is commonly used due to its optimality in a minimum variance sense and the Gaussian[29] kernel function is also

[28] The Epanechnikov kernel is $K(u) = 0.75(1-u^2)$ for $-1 < u < 1$ and zero for $u$ outside that range.

[29] The Gaussian or normal kernel is a kernel with the shape of a Gaussian (normal distribution) curve and

often used due to its convenient mathematical properties. The choice of kernel does not change the estimator significantly while the choice of bandwidth bears the danger of under- or over-smoothing. The most frequently used method of bandwidth selection is to employ the cross-validation criterion by Silverman (1986). However, the choice varies across studies. For example, Ordás Criado and Grether (2011) use the highly robust smoothing parameter proposed by Zhang and Wang (2009).

Kernel density estimation allows the graphical display of distribution trends. Density plots over time are valuable for exploratory and presentational purposes, showing the general changes in the shape of the distribution over time. In addition to kernel densities, various percentiles in emissions distributions are estimated and the spreads in a given interquartile range (IQR) over time are compared. However, in the distribution dynamics approach, it is of particular interest to examine the patterns of persistence and mobility of per capita emissions within the distribution over time. For this purpose Quah (1993b) proposes the transition matrix framework:

$$F_{t+1} = M \cdot F_t \qquad \textbf{(2.5)}$$

where $F_t$ is the cross-sectional distribution of emissions at time $t$, expressed in either the level term, $lnE_i$ or the ratio term, $RE_i=ln(E_i/\overline{E})$. $M$ is a mapping operator which maps $F_t$ into another distribution next time period. Thus, $M$ contains information on the intra-distribution dynamics. Quah assumes that $M$ follows a first-order Markov process with time invariant transition probabilities. Iterating the expression (2.5) $\tau$ times yields:

$$F_{t+\tau} = (M \cdot M \cdot ...M) \cdot F_t = M^\tau \cdot F_t \qquad \textbf{(2.6)}$$

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thus $K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2}$.

As $\tau \rightarrow \infty$, this expression illustrates the long-run steady-state (ergodic) distribution of per capita emissions.

Given the distributions of two time periods, *t* and *t+τ*, the operator *M* in equation (2.6) is approximated by categorising the set of possible values of relative emissions into five bins according to intervals at 1/4, 1/2, 1 and 2. Then each element in the $5\times 5$ Markov chain transition matrix, such as (*j, k*) entry describes the transition probabilities that a country in state *j* at time *t* transits to state *k* at time *t+τ*.

While the matrix *M* represents a discrete-time stochastic process, the transition process can be formulated in a continuous state. Quah (1996) defines a stochastic kernel estimate as the continuous time analogue of the transition matrix, *M*. The stochastic kernel can be described by a conditional density function which shows the relationship between two distributions of emissions at time *t* and $t+\tau$ for $\tau>0$. The cross-sectional distribution of emissions at time *t* is described by the density function, $f_t(x)$. The distribution will evolve over time and the density at time $t+\tau$ is $f_{t+\tau}(x)$. With the assumption that the process of describing the evolution of the distribution is time-invariant and first-order, the relationship between the two distributions can be written as:

$$f_{t+\tau}(y) = \int_0^{+\infty} g_\tau(y \mid x)\, f_t(x)\, dx \qquad \textbf{(2.7)}$$

Let *x* and *y* denote $lnE_i$ or $RE_i = ln(E_i / \overline{E})$ at time *t* and $t+\tau$ respectively. $g_\tau(y \mid x)$ is the conditional density of emissions which describes the conditional probability of a country to move to a specific state at time $t+\tau$, given emissions at time *t*. The goal is the estimation of $g_\tau(y \mid x)$ for $\tau > 0$. The joint, marginal and conditional densities of (*x, y*), *x* and *y*|*x* can be written as $f_{t,t+\tau}(y,x)$, $f(x)$ and $g(y \mid x)$ and the respective kernel estimators are:

$$f_{t,t+\tau}(x,y) = \frac{1}{nh_1h_2}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h_1}\right)K\left(\frac{y-y_i}{h_2}\right) \qquad \textbf{(2.8)}$$

$$f_t(x) = \frac{1}{nh_1}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h_1}\right) \qquad \textbf{(2.9)}$$

and

$$g_\tau(y \mid x) = \frac{f_{t,t+\tau}(y,x)}{f_t(x)} = \frac{1}{h_2}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h_1}\right)K\left(\frac{y-y_i}{h_2}\right) \Bigg/ \sum_{i=1}^{n} K\left(\frac{x-x_i}{h_1}\right) \qquad \textbf{(2.10)}$$

Where $h_1$ are $h_2$ are bandwidth parameters controlling the smoothness for the fit of *x* and *y* respectively. The $K(\cdot)$ plays the same role as in the univariate case in the *x* and *y* dimensions. $g_\tau(y \mid x)$ is called a stochastic kernel. One advantage of this method is that the multimodal densities can be visualised which allows for a clearer understanding of a spectrum of intra-distribution dynamics such as overtaking and catching up or persistence in distributions over time. Another advantage is that the transition matrix or stochastic kernel obtained from historical emissions can be used to forecast the intra-distributional patterns of future emissions for the same cross section.

The fourth approach to convergence focuses on the time-series properties of data. As Carlino and Mills (1996, p.572) point out, beta convergence fails to show how national and region-specific shocks affect different countries or regions over time. If any shocks to relative emissions are persistent over time, the presence of beta convergence cannot indicate a convergence in the cross-country distributions of emissions. Thus, it is particularly of importance to test the time series properties of per capita emissions as a condition for convergence. Carlino and Mills (1993, 1996) use unit root tests to assess whether shocks to per capita income are temporary or not. This approach is called stochastic convergence. The following exposition of stochastic convergence is from List (1999, p.151). The log of relative per capita emissions in region *i* to the cross-sectional mean at time *t*, $RE_{it}$ has two parts; a time-invariant equilibrium level of emissions, $RE_i^0$ and the time deviations from the equilibrium, $u_{it}$:

$$RE_{it} = RE_i^e + u_{it} \qquad \textbf{(2.11)}$$

where $u_{it}$ is a stochastic process which consists of an initial deviation from the equilibrium, $c_{i0}$, a deterministic linear time trend, $\gamma_i t$, and a stochastic disturbance, $\varepsilon_{it}$.

$$u_{it} = c_{i0} + \gamma_i t + \varepsilon_{it} \qquad \textbf{(2.12)}$$

Combining the above two equations yields:

$$RE_{it} = RE_i^e + c_{i0} + \gamma_i t + \varepsilon_{it} \qquad \textbf{(2.13)}$$

If the presence of a unit root in ($RE_{it} - RE_i^e$) is not rejected, emissions of a specific region *i* are considered diverging over time. The Augmented Dickey-Fuller (ADF) test for a unit root is:

$$\Delta RE_{it} = \mu_i + \gamma_i t + \alpha RE_{i,t-1} + \sum_{j=1}^{k} d_j \, \Delta RE_{i,t-j} + \varepsilon_{it} \qquad \textbf{(2.14)}$$

where $\Delta RE_{it}$ is the first difference of relative emissions per capita, $RE_{it} - RE_{i,t-1}$, and $\Delta RE_{i,t-j}$ is the lagged change in relative per capita emissions. The lag length, *k* is usually selected by Akaike Information Criteria (AIC). If the estimated parameter $\alpha$ is zero, then the series contains a unit root and thus any shock to the emission series has permanent effects. The constant $\mu_i$ and $\gamma_i$ are a country-specific intercept and a linear time trend respectively.

The presence of unconditional stochastic convergence requires both $\mu_i$ and $\gamma_i$ are also equal to zero. On the other hand, the stochastic convergence is said to be conditional for country $i$ when $\mu_i$ and $\gamma_i$ are non zero with opposite signs. Even if the null of a unit root for ($RE_{it} - RE_i^e$) is rejected, the same sign on $\mu_i$ and $\gamma_i$ implies divergence of country $i$ from the average emission of cross section. For example, in the case where $\mu_i$>0 and $\gamma_i$>0, country $i$ starts from a higher level of emissions than the average and exhibits an increasing trend of emissions over time which indicates divergence.

In this regard, Carlino and Mills (1993) note that stochastic convergence is a necessary condition but not a sufficient condition for convergence. Therefore, the time-series approach often includes testing the times-series notion of beta convergence which identifies the signs on the initial level and a linear time trend, using the following regression model:

$$RE_t = \mu + \beta t + e_t \qquad \textbf{(2.15)}$$

The time series of relative emissions, $RE_t$, has an initial level, $\mu$ and a deterministic trend, $t$. $\beta$ denotes the average growth of emissions. For an individual cross section, the estimates of $\mu$ and $\beta$ determine the presence of convergence.

There are a bundle of unit root tests employed in the empirical studies on stochastic convergence. Of these, the ADF test and the Kwaitowski-Phillips-Schmidt-Shin (KPSS) unit root test proposed in Kwiatkowski et al. (1992) are the commonly used tests for an individual-country time series while Im, Pesaran and Shin (2003) develop a test for panel data, so called the IPS unit root test. The IPS test and other typical panel unit root tests produce a joint test statistics for the entire panel which is based on the assumption of independence across state-specific series. As Lee and Chang (2008) note, such tests results are not informative to researchers since a rejection of the null does not provide which and how many countries are found stationary or non-stationary.

The presence of structural breaks in the series and endogeneity of the breaks are also considered as potential problems of ADF tests. Numerous test statistics have been developed to deal with cross-sectional dependence in panel data (e.g. Phillps and Sul, 2003) and exogenous or endogenous structural breaks (e.g. Perron, 1997; Zivot and Andrews, 1992; Lee and Strazicich, 2003, 2004).

#### 2.3.2.2 Convergence Studies in Environmental Economics

Initially, the study of pollution convergence in environmental economics relates the issue of convergence to the EKC literature which hypothesises an inverted U-shaped relationship between income and pollution. In the presence of economic convergence,[30] a correlation between income and pollution suggests that countries with the same level of income also converge in emission levels. The Green Solow model developed by Brock and Taylor (2010) also describes emission convergence as a by-product of income convergence. However, such a relationship between growth and emissions may be more applicable to local pollutants such as surphur dioxide ($SO_2$) or suspended particulate matter but less to global pollutants like $CO_2$ which are more expensive to abate and where negative externalities are not restricted to local areas. In other words, improved environmental performance may occur at an even higher level of income for GHGs compared to other pollutants (Holtz-Eakin and Selden, 1995, p.86).

In the other strand of pollution convergence studies which mainly focus on $CO_2$ emissions, the analysis is purely empirical. Nevertheless analyses on the observed distribution and dynamic patterns of $CO_2$ emissions is expected to have great influence on international

[30]Many empirical studies provide strong evidence of beta convergence among OECD countries or industrialised countries (e.g. Barror and Sala-i-Martin, 1991, 1992; Mankiw et al., 1992) while there is lack of evidence on worldwide income convergence (e.g. Sachs and Warner, 1995).

agreements on the equitable allocation of emissions as well as predictions of business as usual carbon emissions and therefore the future extent of global warming. The pro rata allocation of emissions across nations according to population has been advocated from an equity point of view. However, such an equalised target is viable only if per capita carbon emissions across countries exhibit convergence. Moreover, in the absence of convergence, the scheme is distinctly unfavourable to countries with high abatement costs, mostly developed countries since the scheme will involve substantial wealth transfers from developed countries to developing countries through a permit market or relocation of polluting industries (Aldy, 2006, p.535). Therefore, an appropriate analysis of $CO_2$ convergence provides crucial information in negotiating multilateral climate change agreements.

Pettersson et al. (2008) provide a detailed review of literature on emission convergence. More recently, Ordás Criado and Grether (2011) categorise the studies of $CO_2$ emissions convergence according to the methodology employed. Following this approach, I also divide the studies according to three major empirical approaches to convergence: the regression approach to beta convergence, stochastic convergence and distributional analysis. The contribution of this review is to update recent studies and include all pollution types.

**Regression Approach to Beta Convergence**

Only a few papers have looked at beta convergence using the cross-sectional or panel data approach. The earliest study which employs beta convergence for emissions is List (1999). The cross-sectional regression for unconditional beta convergence is used for two indicators of air pollution- $SO_2$ and nitrogen oxide ($NO_x$) across US regions during the period, 1929-1992. For both types of emissions, the coefficient on the initial emissions is statistically significant and negatively related to the growth rate although the size of beta for $SO_2$ is not significantly different from zero.

Strazicich and List (2003) explore beta convergence in the per capita $CO_2$ emissions of 21 developed countries over the period, 1960-1997, conditional on the logarithmic of GDP per capita, its quadratic term, the average price of gasoline, population density and winter temperature. The results indicate strong evidence of beta convergence in both the conditional and unconditional sense. However, none of the explanatory variables are statistically significant except the price of gasoline which was shown to have a negative sign as expected.

Based on the Green Solow model, Brock and Taylor (2010) estimate a regression similar to that of Mankiw et al. (1992) but replacing GDP per capita with emissions per capita. The dataset includes 173 countries over the period, 1960-1998. However, various subsamples are estimated, depending on the availability of data, using explanatory variables such as population growth and the investment share of GDP. The regression results show strong evidence of both conditional and unconditional convergence. Regarding the coefficient estimates on the explanatory variables, both show the expected signs. That is, population growth has a negative effect and investment share has a positive effect on the transition paths to reach a new steady state.

Nguyen Van (2005) tests the presence of unconditional beta convergence in relative $CO_2$ emissions per capita across 100 countries over the period, 1966-1996. The conventional cross-sectional regression is estimated and the results confirm a statistically significant and negative coefficient on the initial emissions.

Stegman and McKibbin (2005) run a cross-section regression of 91 countries over the period, 1950-2000 to test for the presence of unconditional beta convergence. The coefficient on initial emissions is negative and statistically significant at the conventional significance level.

For a smaller sample of OECD countries, the presence of convergence is statistically valid while the speed of convergence is much faster than that of the large world sample.

Pettersson et al. (2008) explore the implications of spatial effects on the measures of beta and sigma convergence. The data cover $CO_2$ emissions per capita of 134 countries over the period, 1990-2005. In addition to the conventional cross-sectional equation for beta convergence, various spatial models are estimated based on three spatial weights matrices: inverse distance, inverse distance-squared and inverse distance-cubed. Before undertaking the regression analysis, Moran's *I* is used to test for any statistically significant clustering among geographically neighbouring countries in terms of the average growth and the initial level of emissions. The results indicate spatial dependence, regardless of a weights matrix chosen. Given this, three spatial process models are estimated: the spatial cross-regressive, spatial lag and spatial error model. For conditional convergence, GDP per capita and dummies for four regional categories are included. The results provide strong evidence of both unconditional and conditional convergence. In general, the spatial terms are statistically significant but only with the inverse-squared and -cubed matrices which give much higher weight to more immediate neighbours. The measure of sigma convergence is also decomposed into spatial dependence and global dispersion, using spatial process models. While the global dispersion indicator is smaller than the conventionally used sample variance over the period as spatial effects are excluded, both indicators decrease over the period, which is robust evidence of sigma convergence.

Ordás Criado et al. (2009) examine the presence of beta convergence of $SO_2$ and $NO_x$ emissions per capita across 25 European countries over the period 1980-2005. The study includes not only GDP per capita but also the growth rate of GDP per capita as explanatory variables. For both pollutants initial emissions are negatively related to the growth of emissions. As expected, the effects of the level as well as the dynamics of per capita GDP are positive. The contribution of this study to the existing literature of beta convergence of emissions is the use of a more flexible functional form, particularly, the partially linear (PLR) additively separable regression model. This model allows unknown nonlinear functions for the initial emissions level and explanatory variables. While the nonparametric approach increases the explanatory power of the model for $NO_x$ emissions, it appears that the linear model fits better for $SO_2$ emissions. Each variable's coefficients are graphically compared using both the parametric and non-parametric regression approaches. The effects of initial emissions for both pollutants are mostly consistent between the two approaches and confirmed the presence of convergence.

Jobber et al. (2010) show that the mean of emissions across 22 EU countries increases over the period, 1971-2006. To examine whether there is emissions convergence the study chooses to test the notion of beta convergence but points out the assumption of homogeneity of all parameters as a limitation of cross-sectional analysis and therefore, proposes a dynamic panel data model which allows for coefficient heterogeneity. However, rather than complete heterogeneity, the parameters are assumed to take an intermediate state between homogeneity and heterogeneity as they are shrunk towards a pooled estimate. To obtain estimates of the 'shrinkage' an iterative Bayesian technique is employed. The empirical results on unconditional convergence show various rates of convergence and volatility across countries. Based on these findings, countries are classified into four groups. To test for conditional convergence, three explanatory variables are also included: GDP per capita, population and the industry's share of GDP. The results show statistically insignificant effects of population across all countries and mixed results for the other two variables. Most notably, the effect of the industry's share of GDP is found statistically significant and positive but only for those countries with the slowest speed of convergence and a growing share of industrial sector in economies.

**Stochastic Convergence**

There is a relatively large literature on testing for the presence of unit-roots in $CO_2$ emissions employing a variety of time series and panel tests. A review of this literature is organised into categories according to the development of unit root tests from individual time series to panel data; and with additional concerns such as structural breaks, cross-sectional dependence and heterogeneity.

While the ADF test is the most widely used unit root test for a country-by-country analysis, Aldy (2006) uses a generalised least squares (GLS) version of ADF test developed by Elliott et al. (1996, DF-GLS test) to improve the power of the ADF test. Furthermore, for the selection of the optimal lag length in the unit root test regression, the Modified AIC is employed as proposed by Ng and Perron (2001). Two sets of countries are tested: 22 OECD countries and 88 world sample. The unit root test results for individual countries show only 13 of 88 countries converged stochastically over the period, 1960-2000. Of these 13 only 3 are OECD countries.

While using country-by-country tests for unit roots, many studies allow for break points to avoid a bias towards accepting the null of no convergence which is likely to occur when ignoring the effect of any permanent shocks on the long-run level of emissions. List (1999) applies the ADF test to $SO_2$ and $NO_x$ emissions across 10 US regions while selecting the lag length endogenously following a sequential procedure proposed by Perron (1989). The results show that 8 regions for $SO_2$ and 9 regions for $NO_x$ diverge from each cross-sectional mean over time. Considering changes in the US pollution regulatory structure during the study period, stochastic convergence is further tested using an ADF-type endogenous break unit root test proposed by Perron and Vogelsang (1992), particularly the innovation outlier (IO) model where structural breaks evolve slowly in intercept and slope. The results do not change for $SO_2$ but two new regions are found converging to the mean for $NO_x$. Regarding break points, three periods dominate: the Great Depression, World War II and the environmental movement of the 1970s.

Lee and List (2004) examine stochastic convergence of the annual US per capita $NO_x$ emissions over the period, 1900-1994. With a various number of lagged terms in the test regressions, two univariate unit root tests are employed: the ADF and PP (Phillips and Perron, 1989) unit root tests. The results of both tests confirm non-stationary series of $NO_x$ emissions. The study also concerns itself with the effectiveness of a specific environmental policy intervention in 1970 on emissions. Thus, a dummy for the year 1970 is included in the PP-type exogenous break unit root test developed by Park and Sung (1994). The results change with a structural break in 1970 as the emission series become trend-stationary. The relationship between environmental policy and emissions are further investigated using ARIMA models.

Lanne and Liski (2004) use an endogenous break unit root test, particularly the additive outlier (AO) model where structural breaks take place suddenly. The choice of the AO model is to test whether oil price shocks of the 1970s have a depressing effect on the emissions trend. Moreover, the test is extended to the case of an unknown number of breaks where each break point is subsequently identified with a subsample that covers only the period after a break found earlier. This procedure is applied to emissions data from 16 developed countries over the period, 1870-1998, which includes the early stages of the industrial revolution. According to the test results, most of statistically significant break points are found in the early 1900s while there is strong evidence that the UK, Sweden and Denmark experience a break in trend around the time of the oil price shock of the 1970s. When considering emissions from only solid-fuel, 10 countries have a stationary process in emissions with one or two breaks. However, not all of these countries have a downward-sloping trend after their breaks. Only 5 countries have a negative trend and thus stochastic convergence.

Bulte et al. (2007) use the minimum LM unit root tests developed by Lee and Strazicich (2003, 2004) to investigate stochastic convergence in the time series of $NO_x$ and $SO_2$ emissions across 48 US states. These tests endogenously determine one or two structural breaks in level and trend while overcoming the problem of size distortions[31] and spurious rejections which remain potentially problematical to ADF-type endogenous break tests. The study further examines time-series beta convergence for those non-stationary countries. The LM test results indicate statistically significant structural breaks and convergence in most individual emissions series for both types of pollutants. However, the regression results for the time-series beta convergence show that for both types of pollutants, only about 50% of states diverge in emissions under the decentralised controls of each state on pollution (before 1970) but converge under the central government controls over states (after 1970).

McKitrick and Strazicich (2005) examine the global average $CO_2$ emissions per cpiata as well as individual emissions series of 121 countries over the period, 1950-2000, using the minimum LM unit root test. The unit root test results for the global average indicate a stationary emissions series with structural breaks in 1968 and 1981. The stationarity of emissions is confirmed by the results of the ordinary least squares (OLS) regression in which emissions are regressed on intercepts and trends for each period identified by two structural

[31] Nunes et al. (1997) show that size distortion occurs due to the assumption of no structural breaks under the null. Lee and Strazicich (2001) also show that the ADF-type endogenous break unit root tests are likely to determine the break at which the bias of the autoregressive coefficient estimates is the greatest.

breaks (i.e. 1951-1968, 1969-1981 and 1982-2000). The results for individual emissions series confirm stationarity in all but 26 countries. According to the regression results for the 95 country series with a structural break in 1978, 46 countries have statistically significant and positive trends after the break while the rest (52%) show either statistically significant and negative trends or insignificant trends i.e. stationary emissions series.

Lee et al. (2008) also employ a break unit root test which allows a simultaneous break in the level and trend to analyse $CO_2$ emissions across 21 OCED countries over the period, 1960-2000. The test results provide strong evidence of convergence in emissions.

Camarero et al. (2011) employ three types of unit-root tests for comparison and robustness of the results for $CO_2$ emissions across 22 OECD countries: the GLS unit root test with MAIC (Ng and Perron, 2001), the Lagrange Multiplier (LM) test for the presence of endogenous breaks and KSS (Kapetanios et al., 2003) test. While the GLS and LM tests formulate the autoregressive structure as linear, the KSS test within the framework of smooth transition autoregressive models adds nonlinearity within the existence of a unit root. Such a specification of nonlinearity attempts to reflect the fact that the release of emissions is highly dependent on the economic cycle. While many studies of the OECD countries are confined to the late 20$^{th}$ century, this study covers the period from 1870 to 2006 which is by far the longest time span. The results provide strong evidence in favour of convergence when the entire period is chosen but no convergence for a shorter time span, 1950-2006.

While the univariate tests like the ADF or KPSS are inefficient for data with a short time span, panel-based tests such as the IPS or Hadri (2000) test are known to possess substantially greater power by averaging univariate tests. The IPS test, for example, tests the unit root null of divergence for the entire panel against the alternative that at least one series is non-stationary.

Heil and Selden (1999) employ both the ADF and IPS unit root tests for the data of 135 countries over the period, 1950-1992. While the ADF results for time series of an individual country display a lack of convergence, the IPS results provide strong evidence of convergence. The study considers an exogenous break point in 1973. The year 1973 is also identified as a break point for GDP time series in the study of Perron (1989). The IPS test is, thus, separately used for the pre-and post-1973 panel data. The results indicate stationarity both before and after 1973.

Strazicich and List (2003) also use the IPS panel unit root test and find strong evidence of convergence in $CO_2$ emissions across 21 industrialised countries. Instead of international data, Aldy (2007) investigates stochastic convergence of $CO_2$, using the IPS panel unit root test. The test results, however, provide no evidence of convergence for 48 US states over 1960-1999.

Nguyen Van (2005) estimates the dynamic panel model by Generalised Method of Moments (GMM) methods developed by Arellano and Bond (1991). The panel model regression without time trend is specified as follows

$$y_{it} = \gamma + \delta\, y_{it-1} + \mu_i + v_{it} \qquad \textbf{(2.16)}$$

where $y_{it}$ is the log of relative emissions of country $i$ at period $t$ and $\mu_i$ is the country specific effect. Following Islam (1995), $\delta$ has a relation with the speed of convergence, $\lambda$ which can be obtained in the cross-sectional beta convergence, as such $\delta = e^{-\lambda\tau}$ where $\tau$ is the time interval length. Thus, the speed of convergence is estimated using the above dynamic panel model with 5- and 10-year intervals. The panel regression results of the equation (2.16) provide strong evidence of convergence and produce a higher rate of convergence than simple cross-sectional regression.

Since the presence of contemporaneous correlation between cross-sectional observations as well as heterogeneity may lead to false rejection of the unit root null, later studies on stochastic convergence attempt to deal with these issues which are ignored in the IPS unit root test. Particularly, the rejection of the IPS test null does not provide any information on precisely which panel members are stationary or non-stationary. In this regard, Lee and Chang (2008) use a new panel unit root test, the Seemingly Unrelated Regressions Augmented Dickey-Fuller (SURADF) test proposed by Breuer et al. (2002). In contrast to typical panel unit root tests, the SURADF test provides results for each time series while allowing for contemporaneously correlated errors, heterogeneity in the autoregressive parameters, heterogeneous fixed effects and heterogeneous lags for each panel member. Out of 21 OECD countries over the period, 1960-2002, 7 countries are identified as convergent in the log of relative $CO_2$ emissions per capita. Varying results across countries reveal a problem of misleading inferences which are biased towards stationarity when ignoring heterogeneity.

Before using the SURADF test, Camarero et al. (2008) employ the multivariate ADF test developed by Sarno and Taylor (1998) which tests the joint null hypothesis of zero autoregressive parameters across the cross section. Instead of one particular pollutant, Camarero et al. (2008) construct two environmental performance indicators (EPIs) and examine whether 21 OECD countries are catching up with the performance of Switzerland as the benchmark country. The results show that with one indicator all OECD countries are converging on the performance of Switzerland during the period, 1971-2002 but for the other indicator, there are 15 catching-up countries.

Similarly, Sek (2010) employs the SURADF unit root test for correlated and heterogenous cross sections and compares the results with those of the typical panel unit root tests, such as the IPS test. One distinct feature of this study is the comparison of relative $CO_2$ emissions series for Malaysia to the world mean, the mean of high, middle and low income countries, South-Asia countries and European countries. In addition to emissions per capita, emissions per dollar GDP and per dollar oil price are also checked for a unit root. The results show that most series are stationary but relative emissions per capita and per dollar GDP to the mean of low income countries were non-stationary, which suggests divergence from the low values but convergence towards all the other means.

Romero-Ávila (2008) employs tests which take stationarity as the null hypothesis, such as the univariate KPSS test and the panel test of Hadri (2000) to investigate stochastic and deterministic convergence[32] of $CO_2$ emissions of 21 OECD countries over the period, 1960-2002. The results of the above tests are compared with the panel test developed by Carrion-i-Silvestre et al. (2005, CBL test) which allows for an unknown number of structural breaks. Furthermore, the bootstrap distribution of the CBL test is computed to control for cross-sectional dependence as well as heterogeneity in the estimation of the long-run variance following Maddala and Wu (1999). The analysis particularly focuses on two elements in the specification of tests: structural breaks and cross-sectional dependence. Remarkably, the results critically depend on the inclusion of structural breaks in the specifications of stationarity tests. Without structural breaks, the results of the KPSS tests show divergence of 10 countries while the result of the Hadri (2000) test reveals an overall pattern of divergence from the mean. However, the KPSS tests with structural breaks indicate the presence of convergence to the mean in most countries except Germany. The presence of stochastic and deterministic convergence across OECD countries is further confirmed by the CBL test

[32] The notion of deterministic convergence is introduced by Li and Papell (1999) as a stronger form of convergence than stochastic convergence by excluding both deterministic and stochastic trends in the regression of unit root tests ($\mu_t$ and $t$ in the equation (2.14))

results with cross-dependence while the inclusion of heterogeneity in the estimation of the long-run variance does not change the results.

Lee and Chang (2009) also use the CBL panel test for multiple structural breaks while allowing for any kind of cross-sectional dependence among 23 OECD countries over the period, 1950-2002. The results are compared with various panel-based tests without breaks, such as the Hadri (2000), the IPS, the test by Levin et al. (2002, LLC) and the Fisher-ADF and Fisher-PP tests proposed by Maddala and Wu (1999). The results are consistent with Romero-Ávila (2008). That is, the results of tests without structural breaks generally indicate non-stationary $CO_2$ emissions series while the results of both individual series and panel-based tests with structural breaks show stationarity of the series and thus the presence of stochastic convergence. This is also confirmed by the results of the CBL test specified to include heterogeneous and correlated cross sections.

Barrasi et al. (2008) explicitly test for the presence of cross-sectional correlation by means of the cross-sectional dependence (CD) test statistic of Pesaran (2004) before applying any robust tests to tackle heterogeneity and cross-sectional dependence. The analysis starts with the time-series concept of beta convergence in which an initial deviation from the equilibrium and a time trend have to be opposite in sign. Using heteroscedastic and autocorrelation corrected (HAC) regressions proposed by Vogelsang (1998), the sign and magnititude of the constant and time trend are obtained for each series of relative emissions per capita over the period, 1950-2002. The results identify 20 out of 21 OECD countries as convergent. Then, commonly used tests of both the null of stationary (e.g. KPSS and the Hadri (2000) test) and the null of a unit root (e.g. the DF and IPS test) are applied to examine stochastic convergence of this group of countries. While the results of both univariate and panel-based tests provide no evidence of stochastic convergence, the CD test statistic suggests a bias can occur due to cross-sectional dependence. Therefore two robust tests, which take into account not only heterogeneity but also cross-sectional dependence, are utilised: the HLM stationarity test developed by Harris et al. (2005) and the BD robust unit root test developed by Breitung and Das (2005). The results of both tests strongly suggest a lack of stochastic convergence.

Barrasi et al. (2011) employ the standard stationarity or unit root tests, such as the KPSS and ADF unit root tests, but find mixed evidence of convergence across 18 OECD countries over the period, 1870-2004. In the second stage of the analysis, the authors allow for the possibility of long memory in emissions series since the determinants of $CO_2$ emissions, such as the scale and composition of the economy or regulations, tend to change only slowly. The characterisation of relative emissions series as a potentially fractionally integrated process displaying long memory is accomplished using the Local Whittle (LW) estimator (Robinson, 1995) of the fractional integration parameter and its variations (i.e. Exact Local Whittle (ELW) and Feasible Exact Local Whittle (FELW)) (Shimotsu and Phillips, 2005, 2006). The results of these tests provide strong evidence that 13 of 18 countries are converging whilst there was no evidence for 5 other countries.

Westerlund and Basher (2008) employ three panel unit root tests which allow for heterogeneity of the cross section. Such as a test developed by Phillips and Sul (2003). They use a factor model which decomposes the observations across nations into a common trend and an idiosyncratic component. The model is used to test the hypothesis of convergence in the idiosyncratic component and/or common factor. The results provide strong evidence of convergence for the entire panel of 16 OECD countries and a larger sample of 26 countries over the period 1870-2002 and 1901-2002 respectively. Furthermore, the study finds that the speed of convergence is similar across countries.

Panopoulou and Pantelidis (2009) also apply a factor model developed by Phillips and Sul

(2007) which incorporates transitional heterogeneity and convergence across 128 countries in $CO_2$ emissions per capita over the period, 1960-2003. While there is evidence of stochastic convergence among all countries in the early period, countries are divided into two convergence clubs in later years, either with high levels or low levels of emissions per capita. The authors further investigate the existence of convergence among different economic and geographical groups of countries. For example, within the Economic and Monetary Union (EMU) of the EU, the OECD and a group of high-income countries, the members of each group converge whilst middle-income countries display a slower convergence among themselves and low-income countries diverge. The study also provides interesting evidence that the two clubs converge slowly while some countries move from one club to the other.

**Distributional Analysis**

Holtz-Eakin and Selden (1995) and Heil and Wodon (2000) project the distribution of $CO_2$ emissions according to the level of income, based on the evidence of the EKC hypothesis and income convergence of large international data obtained within the study. The EKC analysis proposes a diminishing marginal propensity to emit as economies develop and this will be particularly apparent in high income countries. However, low income countries will rapidly increase per capita emissions and take a significant share of global emissions. Holtz-Eakin and Selden (1995) argue that the presence of convergence in the long run may depend on three factors: the diminishing marginal propensity to emit in high income countries, the initial gap between high and low income countries and how long it takes for middle countries to achieve the income level at which their emissions turn downwards. Furthermore, Heil and Wodon (2000) use the Gini index to show the evolution of inequality in per capita emissions across countries over time. The forecasts of the index till 2100 show a decline in the inequality of emissions between different income groups and thus support the presence of convergence in the long term.

Later studies widely employ nonparametric methods for the analysis of distributional dynamics. Aldy (2006) employs histograms and IQR estimates for relative $CO_2$ emissions per capita to the global average in addition to the estimates of the annual standard deviation of emissions for sigma convergence. Both cross-sectional analyses and standard deviations show divergence in the 88 world sample but convergence in 22 OECD countries. Particularly, the IQR estimates of the world sample increase over the period and the difference between the values of later and initial periods is statistically significant, which implies the tails of the emissions distribution move further away from each other thus suggesting emissions divergence. According to the analysis of the transition matrix, there are high probabilities of persistence, particularly in the pattern of low and high values of emissions which also suggests the lack of convergence of emissions to the mean.

Aldy (2007) also employs the transition matrix framework to show distribution dynamics of 48 US states in relative $CO_2$ emissions per capita. The estimates of the transition matrix show persistent differences in the emissions distribution and little movement towards the national mean and thus no convergence.

Nguyen Van (2005) uses both kernel density estimates and stochastic kernel methods to investigate the dynamics of the entire cross-section distribution for 100 countries and 26 industrialised countries over the period, 1966-1996. There is convergence in relative $CO_2$ emissions per capita among industrialised countries as we can observe a tendency of low (high) values to increase (decrease) over the period. With the world sample, less polluting countries than the global mean show persistence in their relative performance while heavy polluting countries reduce their emissions close to the global mean.

Stegman (2005) and Stegman and McKibbin (2005) examine 97 countries over the period, 1950-1999. Firstly, various summary measures are used to test for sigma convergence of $CO_2$ emissions per capita across countries over the period. In addition to commonly used dispersion measures such as the SD, CV, IQR, the average and median absolute deviation (AAD and MAD) are employed. All the measures show increasing dispersion over the period except for the coefficient of variation (CV). Secondly, kernel density estimates and stochastic kernel estimates are computed for the level deviations (i.e. $E_i - \overline{E}$) as well as proportional deviations from the average (i.e. $E_i / \overline{E}$). From the visual illustration of kernel estimates, the distribution of both measures of emissions per capita changes significantly over the period, in general to more flattened shapes with a wider range. The mobility of the distribution from stochastic kernel estimates shows some different features for the two measures of emissions. For the level deviations, there is high persistence of countries particularly located far above and far below the average emissions whilst the proportional deviations show an increase in relative emissions over the entire distribution and particularly a greater upward mobility in very high values. Despite some differences in distributional features between two measures, in general, persistent gaps of countries in $CO_2$ emissions per capita are observed.

Ezcurra (2007) studies the spatial distribution of per capita $CO_2$ emissions across 87 countries over the period, 1960-1999. Firstly, a decrease in the CV over the period indicates the presence of sigma convergence. Secondly, kernel density estimates over the period show a tendency of moving towards the global average level of emissions. Thirdly, the degree of polarisation between two or three groups is measured using an indicator proposed by Esteban et al. (1999). The evolution of cross-country polarisation shows that the gap between groups decreases over the entire period, except the 1960s. Finally, intra-distribution mobility is analysed using the stochastic kernel technique. The results are similar to the case of the large international sample in Nguyen Van (2005). That is, countries with very high levels of emissions tend to converge towards lower levels while those in intermediary levels of emissions tend to stay in the same position. This suggests the importance of the role played by those heavy polluting countries in accelerating the process of convergence.

Ordás Criado et al. (2009) examine the intra-distribution of $SO_2$ and $NO_x$ emissions per capita across 25 European countries, using kernel density estimates and stochastic kernels. According to kernel estimates, the distribution of both pollutants apparently moves to a single-peaked and more concentrated shape over the period, 1985-2005. This is further confirmed by a peaked and unimodal shape of long-term distribution based on conditional density estimates computed over different intervals of time.

Ordás Criado and Grether (2011) examine a large world dataset which includes 166 countries over the period, 1960-2002. Various non-parametric methods are employed to examine inter- and intra-distribution of $CO_2$ emissions per capita expressed in both level and relative terms. In addition to indicators for the spread, asymmetry and peakedness, two distributional tests are employed to compare shapes of distribution between two successive periods: the Kolmogorov-Smirnov test (KS test) and the Li (1966) test. The null of the KS test is the identical shape of two distributions at time $t$ and $t+\tau$. The Li (1996) test accounts for cross-sectional dependencies between two distributions. According to the results of the indicators and the tests, there is a significant change in the distribution in the earliest decade, usually with strong divergence, followed by moderate divergence in the 1970s and stabilisation afterwards. The kernel density estimates of $CO_2$ emissions per capita in 2000 is compared with the distribution of future values obtained using stochastic kernel estimates computed based on different intervals of time (i.e. 1960-2002, 1970-2002, 1980-2002, 1980-2002 and 1990-2002). Both level and relative terms of emissions are expected to diverge globally and stabilise at higher levels in the long term. The analysis on sub-group convergence is conducted using the same measures and statistics. While several economic and geographical clusters of countries are identified as convergent groups (e.g. Europe and OECD over the period, 1960-2002 and high- and middle-income economies, Latin America and Caribbean and Sub-Saharan Africa over the period, 1980-2000), the study finds no evidence of multi-polarisation in converging patterns.

Table 2.2 summarises the studies on pollution convergence reviewed so far. The empirical results on emission convergence vary according to methods and data used across studies. As can be seen, these studies examine the presence of convergence mainly in $CO_2$ emissions for different sets of countries which include either only industrialised countries or a large number of countries regardless of economic status. Some studies like Aldy (2007) focus on regional convergence using emissions data across US states. The study period usually covers at least the second half of the 20$^{th}$ century but data series also date back up to 1870 in the studies for a few industrialised countries.

The majority of studies apply stochastic convergence tests (21 out of 31 studies) while increasingly addressing issues like structural breaks, cross-sectional dependence and heterogeneity across countries. Only a few studies apply beta convergence test (6 studies) but various estimation methods are proposed such as spatial process models, the partially linear regression model and Bayesian estimation method. The analysis of distribution dynamics (8 studies) mostly utilises stochastic kernels.

As Craido and Grether (2010) conclude, distributional analyses tend to produce some evidence of divergence in per capita emissions for large international data but convergence among developed or large emitters. Interestingly, this is consistent with empirical findings on the pattern of economic convergence and thus may suggest some correlation between

**Table 2.2: Empirical surveys of convergence studies in environmental economics**

| Authors and year | Pollutant | Time series | Cross section | Type of convergence | Methodology | Findings |
|---|---|---|---|---|---|---|
| 1. **Holtz-Eakin and Selden (1995)** | $CO_2$ | 1951-1986 | 130 | EKC and distribution | Panel data analysis with income | Divergence |
| 2. **Hel and Selden (1999)** | $CO_2$ | 1950-1992 | 135 | Stochastic | ADF | Convergence for 20/22countries (levels/log) |
| | | | | | IPS separately for pre-and post-1973 | Convergence |
| 3. **List (1999)** | $SO_2$, $NO_x$ | 1929-1994 | 10 US regions | β-convergence | Cross-sectional OLS | Convergence |
| | | | | Stochastic (SB) | ADF, IO | Divergence of both type of emissions for 8 regions |
| 4. **Heil and Wodon (2000)** | $CO_2$ | 1950-1992 | 135 | EKC and distribution | -Panel data analysis with income<br>-Gini index | Convergence |
| 5. **Strazicich and List (2003)** | $CO_2$ | 1960-1997 | 21 | β-convergence | Cross-sectional OLS | Convergence |
| | | | | Stochastic | IPS | Convergence |
| 6. **Lanne and Liski (2004)** | $CO_2$ | 1870-1998 | 16 | Stochastic (SB) | AO model | Convergence for 5 countries |
| 7. **Lee and List (2004)** | $NO_x$ | 1900-1994 | US | Stochastic (SB) | ADF, PP, PS (1994) | Convergence with the 1970 structural break |

| | | | | | | |
|---|---|---|---|---|---|---|
| **8. Stegman (2005)** | $CO_2$ | 1950-1999 | 97 | σ-convergence | CV, SD, AAD, MAD, IQR | Increasing except CV |
| | | | | Distribution dynamics | Kernel<br>Stochastic kernel | Persistence |
| **9. Stegman and McKibbin (2005)** | $CO_2$ | 1950-1999 | 97 | σ-convergence | CV, SD, AAD, MAD, IQR | Increasing except CV |
| | | | | β-convergence | Cross-sectional OLS | Convergence |
| | | | | Distribution Dynamics | Kernel<br>Stochastic kernel | Persistence |
| **10. McKitrick and Strazicich (2005)** | $CO_2$ | 1950-2000 | 121 | Stochastic (SB), | LM unit root | Convergence for the global average emissions series and for 49 individual countries |
| | | | | Time-series β-convergence | Time-series OLS | |
| **11. Nguyen Van (2005)** | $CO_2$ | 1966-1996 | 26<br>100 | Distribution dynamics | Kernel<br>Stochastic kernel | Convergence for 26 industrialised countries but partial convergence for 100 countries |
| | | | | β-convergence | Cross-sectional OLS | Convergence |
| | | | | Stochastic | Panel GMM method by Arellano and Bond (1991) | Mixed depending on time interval chosen |
| **12. Aldy (2006)** | $CO_2$ | 1960-2000 | 23<br>88 | σ -convergence | SD | Convergence (23 OECD)<br>Divergence (88) |
| | | | | Distribution dynamics | Histogram<br>IQ<br>Transition matrix | |
| | | | | Stochastic | DF-GLS | Convergence for 13 countries (inclusive 3 OECD) |

| | | | | | | |
|---|---|---|---|---|---|---|
| **13. Aldy (2007)** | $CO_2$ | 1960-1999 | 48 US states | Distribution dynamics | SD<br>Kernel density<br>Transition matrix<br>IQR | Divergence |
| | | | | Stochastic | IPS | Divergence |
| **14. Bulte et al. (2007)** | $SO_2$, $NO_x$ | 1929-1999 | 48 US states | Stochastic (SB) | LM unit root | Divergence before 1970<br>Convergence after 1970 |
| | | | | Time-series β-convergence | Time-series OLS | Diverging 52% and 44% of states in $SO_2$ and $NO_x$ respectively |
| **15. Ezcurra (2007)** | $CO_2$ | 1960-1999 | 87 | Distribution dynamics | Kernel density<br>Polarisation measure<br>Stochastic kernel | Convergence |
| **16. Romero-Ávila (2008)** | $CO_2$ | 1960-2002 | 23 OECD | Stochastic | -KPSS with and without SB,<br>-Hadri (2000) and CBL with and without CD | Convergence (CBL with CD) |
| **17. Westerlund and Basher (2008)** | $CO_2$ | 1870-2002<br>1901-2002 | 16 OECD<br>38 | Stochastic (SB, CD) | Factor model by PS (2003), MS (2004) and BN (2004) | Convergence |
| **18. Barassi et al. (2008)** | $CO_2$ | 1950-2002 | 21 | Time-series β-convergence | Time-series OLS | Convergence for 20 countries |
| | | | 20 | Stochastic | -KPSS, DF<br>-Hadri (2000), IPS, HLM, BD robust | Divergence |
| **19. Camarero et al. (2008)** | $CO_2$ | 1971-2002 | 22 OECD | Stochastic (CD) | Multivariate ADF, SURADF | -Convergence for 21 countries in EPI1<br>-Convergence for 15 countries in EPI2 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **20. Lee and Chang (2008)** | $CO_2$ | 1960-2002 | 21OECD | Stochastic (CD) | -ADF, PP, DF-GLS, NP<br>-LLC, UB, IPS, Fisher-ADF, Fisher-PP, SURADF | Convergence for 7 countries |
| | | | | Time-series β-convergence | Time-series OLS | |
| **21. Lee et al. (2008)** | $CO_2$ | 1960-2000 | 21 OECD | Stochastic (SB) | Sen (2003) | Convergence |
| **22. Pettersson et al. (2008)** | $CO_2$ | 1990-2005 | 134 | σ-convergence | Sample variance<br>Global dispersion from spatial process | Convergence with varying spatial dependence over time and over regions |
| | | | | β-convergence | Aspatial and spatial cross-sectional model OLS, ML, IV | Convergence |
| **23. Lee and Chang (2009)** | $CO_2$ | 1950-2002 | 21 OECD | Stochastic (SB, CD) | -KPSS with SB,<br>-LLC, UB, IPS, Hadri (2000), Fisher-ADF, Fisher-PP, CLB with and without CD | Convergence (KPSS with SB, CBL with CD) |
| **24. Panopoulou and Pantelidis (2009)** | $CO_2$ | 1960-2003 | 128 | Stochastic (CD) | Time-varying factor model by PS (2007) and club-convergence identification algorithm | Convergence (1960-82)<br>Two clubs (1975-2003) |
| **25. Ordás Criado et al. (2009)** | $SO_2$, $NO_x$ | 1980-2005 | 25 EU | β-convergence | Parametric and nonparametric regressions (PLR) | Convergence<br>Convergence |
| | | | | Distribution | Kernel density<br>Stochastic kernel | Convergence |
| **26. Jobert et al. (2010)** | $CO_2$ | 1971-2006 | 22 EU | β-convergence | Bayesian shrinkage estimation method | Convergence to slightly higher level |

| | | | | | | |
|---|---|---|---|---|---|---|
| **27. Sek (2010)** | $CO_2$ | 1971-2006 | Malaysia relative to different regional mean | Stochastic (CD) | LLC, UB, ADF-Fisher, Fisher-PP, IPS, SURADF | Convergence to high levels but divergence to low levels of regional means |
| **28. Brock and Taylor (2010)** | $CO_2$ | 1960-1999 | 22 OECD | β-convergence | Cross-sectional OLS | Convergence |
| **29. Ordás Criado and Grether (2011)** | $CO_2$ | 1960-2002 | 166 | σ-convergence | Variance | Divergence followed by convergence |
| | | | | Distribution | IQR, Asymmetry, Peakedness, multimodality, shape equality<br>Kernel density<br>Stochastic density | Global divergence<br>Club convergence (geography, income level) |
| **30. Camarero et al. (2011)** | $CO_2$ | 1870-2006<br>1950-2006 | 22 OECD | Stochastic | Linear UR (NP, LM)<br>Non-linear (KSS) | Convergence (1870-2006)<br>Divergence (1950-2006) |
| **31. Barassi et al. (2011)** | $CO_2$ | 1870-2004 | 18 OECD | Stochastic | ADF, KPSS, NP | Mixed across the tests |
| | | | | | LW, ELW, FELW | Convergence for 13 countries |

*Notes*: AAD=Average absolute deviation, ADF=Augmented Dickey-Fuller, AO model=Additive outlier model. BD=the test of Breitung and Das (2005), BN (2004)=Bai and Ng (2004), CBL=the test of Carrion-i-Silvestre et al. (2005), CD=Cross-sectional dependence, CV=Coefficient of variation, DF-GLS= GLS version of ADF (Elliot et al., 1996), (F)ELW=(Feasible) Exact Local Whittle (Shimotsu and Phillips, 2005, 2006), EPI=Environmental Performance Indicator, HLM=the test of Harris et al. (2005), IQR=Interquartile range, KPSS=Kwaitowski-Phillips-Schmidt-Shin unit root test, KSS=Kapetanios et al. (2003), LLC test=the test of Levin et al. (2002), LW=the Local Whittle (LW) estimator (Robinson, 1995), MAD=Median absolute deviation, MS (2004)=Moon and Perron (2004), NP=test of Ng and Perron (2001), PLR=the partially linear additively separable regression model, PP=Phillips-Perron unit root test, PS (1994)=the test of Park and Sung (1994), PS (2007)= Phillips and Sul (2007), PS (2003)=Phillips and Sul (2003), SB=structural breaks, SD=standard deviation, SURADF=Seemingly Unrelated Regressions ADF UB=the test of Breitung (2000), UR=unit root test.

distributions of growth and emissions. On the other hand, time series analyses show the opposite results with regard to the group of countries which converge in emissions.

### 2.3.3 Spatial Effects in Convergence Studies

Spatial econometric methods have traditionally been utilised only in specialised fields such as regional science but in recent years, have crossed over into mainstream economics. Especially in the last decade, there has been an exponential growth in the literature taking account of spatial effects in the analysis of economic convergence (e.g. Bernat, 1996; Rey and Montouri, 1999; Fingleton, 1999, 2001, 2004; Lopez-Bazo et al., 1999). The greater availability of spatial econometric software has enabled the empirical economic growth literature to estimate and test spatial interaction and specify models based on various spatial process models. Abreu et al. (2005) review the literature on spatial econometrics and economic growth, and assess the appropriateness of such techniques in convergence studies.

Numerous studies of regional economic convergence have included spatial externalities. The endogenous growth theory and new economic geography models provide a theoretical background for the role of spatial externalities in the process of regional growth (e.g. Romer, 1986; Lucas, 1988; Tamura, 1991; Mankiw et al., 1991; Fujita et al., 1999). While the neoclassical growth model assumes that technology is outside or exogenously given to the economic system, the new growth literature recognises the diffusion of knowledge across countries or regions as a key component of technological progress. Unlike the neoclassical model, this explains observed persistence in income disparity or agglomeration of economic activities across geography. The underlying theoretical rationale for externalities is that observations are linked to each other to some extent. No longer is it assumed that an individual region is a homogeneous and independent entity. Primarily, regional interactions occur more intensively among geographically close areas. In other words, geographical location is a crucial factor which determines the extent of externalities. This idea is clearly expressed in the Tobler's first law of geography that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p.3). Based on this notion, the presence of spatial effects in the form of autocorrelation or heterogeneity may accelerate or decelerate the process of convergence.

In the regression analysis of income convergence, the presence of spatial dependence can be specified using either a spatial lag in the error term and/or a lag in the dependent variable. The assumption of each model differs in terms of externality mechanisms whether neighbourhood effects arise through the transmission of random shocks from neighbours or through spatial interactions which reinforce technological diffusion and pecuniary externalities. Empirical growth literature assumes that the latter form of spatial effect is relevant to externalities in the process of endogenous growth. However, most studies found the presence of spatial effects in the form of nuisance rather than substantive spatial dependence. Fingleton and López-Bazo (2006) note that such results are often obtained when no conditioning variables are included in the regression (e.g. Armstrong, 1995; Rey and Montouri, 1999; Baumont et al., 2001). Hence, the preference for the spatial error model may be indicative of omitted variables which are spatially autocorrelated.

While the analysis of spatial effects in convergence is mostly based on the beta convergence equation, Rey and Dev (2006) decompose an indicator of sigma convergence into global dispersion and a spatial component. Using US regional income data, the study shows the evolution of spatial autocorrelation and its significant influence on the bias of the sample variance.

Overall, there is strong evidence of spatially autocorrelated income series but the mechanism of its effect in the process of convergence is empirically ambiguous. Emissions data may also mask nontrivial geographical patterns due to the spatial dimension which in turn results inefficient estimation of parameters in beta convergence equations. Pettersson et al. (2008) is the only emissions convergence study which takes into account spatial dependence in world $CO_2$ emissions data. The study applies spatial process models in both beta and sigma convergence. Based on the goodness of fit across different spatial models for the conditional beta convergence, the spatial lag model fits the emissions data better than the spatial error model. In other words, a country's emissions growth is directly affected by growth in neighbourhoods.

## 2.4 Research Objectives

In this paper, using recycling rates across local authorities in England, the following three claims are tested. Firstly, there is catching-up between local authorities in terms of their recycling performance which may arise from strategic interaction among local authorities. Secondly, the newly implemented market-based instruments since 2005 may improve the overall performance and also speed up the rate of convergence among local authorities. Finally, due to the spatial nature of the interaction, there will be spatial autocorrelation in recycling performance and this may also influence the process of convergence.

Though it is largely neglected, spatial spillovers could be an important factor in recycling performance across local authorities. The main channel for spatial effects could be imitation of the superior local authorities in recycling performance. In productivity spillovers literature, this is called as demonstration effects which allow domestic firms to observe and learn multinational firms' superior knowledge and technology (e.g. Teece, 1977; Blomström and Kokko, 1998). This could be applied to waste management performance which varies across local authorities. With increasing pressure to increase recycling and greater incentive to reduce landfill reliance, authorities will imitate those who are successful at recycling as they may demonstrate (intentionally or otherwise) to other authorities how to be successful at recycling.

The literature on local government behaviour emphasises strategic interaction as a main channel for spatial spillovers. Brueckner (2003) summarises the literature on strategic interaction across local governments. One strand of literature on strategic interaction is related to competition among local governments by setting tax rates or benefit levels based on mobile population that seek out lower tax rates or greater welfare benefits i.e. tax- and welfare-competition models. Other literature focuses on strategic choice of environmental standards by local governments based on capital mobility which may lead to lax environmental regulations i.e. the possibility of a 'race to the bottom' (Wilson, 1996).

Whilst these approaches emphasise the competition for mobile resources and their flows across local governments, strategic dependence may also occur due to informational spillovers from other local governments and electoral competitions. In the yardstick competition model developed by Besely and Case (1995),[33] local residents evaluate the quality of public service provision by their own local governments based on performance of other governments as a yardstick. Given such information spillovers, incumbents in each local authority have an incentive to move towards better technologies chosen in their reference authorities, in order to avoid electoral defeat. This type of strategic interaction is the most relevant for recycling performance across local authorities. Furthermore, this, as proposed in growth literature, provides a theoretical perspective on convergence. That is, the inflow of knowledge from advanced regions is a key factor underpinning the progress in

[33] Using US state data from 1960 to 1988, Besley and Case (1995) estimate the impact of the tax change in neighbouring states as well as that in their own states on the probability of reelection. The results support the existence of yardstick competition in taxation across US states, such that reelection-seeking incumbents are sensitive to relative performance on taxation. Therefore, reelection is negatively correlated to tax increases in their own jurisdiction but positively correlated with tax increases in neighbouring jurisdictions. In addition, tax changes in neighbouring states are positively correlated.

regions that initially fall behind.

In waste management, the evaluation of relative performance has become more important to monitor progress towards national and local targets for landfill diversion and recycling rates under the EU Landfill Directive and Waste Strategy. This guarantees the presence of informational externalities across local authorities and in turn yardstick competition to achieve targets using the most cost-efficient method of collecting waste and sorting recyclables. Although some exogenous characteristics which vary across local authorities require different schemes for cost-efficiency, the presence of yardstick competition will be a potentially important source of convergence in waste management performance as well as overall improvement in performance.

Moreover, a recent change in the national waste policy towards incentive-based instruments (e.g. the LATS and Landfill Tax Escalator) enables local authorities to take a more proactive and cost effective approach to divert waste and increase recycling activities by creating rewards for every tonne of waste diverted from landfills by tax and permit savings. In addition to cost effectiveness, one notable advantage of market-based instruments is dynamically efficient pattern of incentives. In other words, there are countinuously more incentives for the development and adoption of new technologies. In waste management, newly implemented market-based instruments may reinforce yardstick competition in local authorities' decisions on waste management practices. That is, local authorities have more incentive to exploit knowledge externalities from advanced ones in recycling performance as a way to improve their waste management performance and thus save their tax and permit payments on landfill disposal. This may speed up the diffusion of best practices across local authorities and thus convergence dynamics in recycling activities i.e. a faster rate of convergence.

Various notions of convergence using different methods reviewed in the previous section are applied to recycling rates both in level terms and relative terms. Sigma convergence, beta convergence and distribution dynamics are all investigated. Stochastic convergence cannot be examined due to a short time series of recycling rates. The test results for various measures of convergence are compared to identify the presence and any peculiar features of convergence or divergence patterns.

Finally, local authorities can be seen as a spatial unit and thus it is necessary to accommodate geographical components in the cross-sectional distribution of recycling rates. In particular, the interaction among local authorities through information spillovers involves spatial nature as proximity is an important factor in selection for benchmark local authorities. This implies geographically closer units are more likely to converge. Indeed, empirical studies on yardstick competition consistently provide the evidence of spatial interdependence in the efficiency measure of decentralised public services (Revelli and Tovmo, 2007). The spatial distance between local authorities is also seen as a proxy variable that represents the strength of linkage between them. For example, it may determine the magnitude of positive spillovers from well-performing authorities to poor-performing authorities. To test such a hypothesis, I investigate the presence of spatial clustering in recycling performances. It is also of interest to examine whether the implementation of the LATS and a higher landfill tax rate changes the existence and extent of spatial interaction across local authorities. As the newly implemented market-based policy insturmnets are expected to stimulate externalities across authorities, local authorities in each cluster are likely to become more similar in their recycling performance i.e. an increase in spatial dependence.

Furthermore, the presence of spatial effects is taken into account in beta and sigma convergence to examine the nature of spatial externalities and their impacts on the speed of convergence. This approach is in line with the work of Pettersson et al. (2008) where spatial explanatory analysis is applied to $CO_2$ emissions and spatial effects are taken into account in the process of convergence using spatial process models. Detailed techniques in spatial econometrics are described in the section of spatial data analysis.

## 2.5 Data

DEFRA conducts an annual Municipal Waste Management Survey, requesting local authorities to complete a questionnaire about their performance in waste management. The data collected from the survey have been used to monitor the trends in waste and waste management practices. After the introduction of the EU Directive and Waste Strategy in England, the survey results have been an important means of measuring progress towards the targets across local authorities.

Of the total waste arising in the UK, waste from construction sites accounts for about half, industry and commerce take a third whilst a relatively small fraction of waste is generated at the household level, taking only a sixth of the total waste arising in the UK in 2002/03. Non-household sources of waste however are recycled or reused nearly half of their arising.[34] Thus there is greater urge and scope to increase household recycling. As national targets of recycling/reuse under EU directives are applied at a local authority level, household recycling rates can be taken as a good indication of waste management performance across local authority.[35]

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[34] In 2002/2003, 50% of waste from construction is recycled by crushers and screeners and a further 18% is spread on exempt sites such as reclamation, agricultural improvement or infrastructure projects. During the same period, 42% of commercial and industrial waste is recycled or reused while only 18% of household waste is recycled, reused and composted.

[35]The household waste data include small amounts of trade and commercial waste collected with household waste from rounds covering premises with mixed uses and from trade and commercial waste at civic amenity sites (DEFRA, 2005). A civic amenity site is a facility where the public can dispose of waste and also often containing recycling points. It is estimated to be 5 percent of household waste; however, the DEFRA does not

In this study, I utilise household recycling (including composition) rates measured in weight across local authorities in England. There are 394 local authorities in England, which have statutory responsibility for collecting and/or disposing of household waste. Depending on their primary responsibility in waste management, they are classified as Waste Collection Authorities (WCAs), Waste Disposal Authorities (WDAs) or Unitary Authorities (UAs). All district councils (273) are WCAs which have a duty to collect at least two types of recyclable waste from households under the Household Waste Recycling Act 2003. All county councils (40) are WDAs which arrange the disposal and recycling of waste collected from WCAs. Thus WDAs provide recycling facilities and manage landfill sites while developing and implementing plans for sustainable waste management. All unitary councils (81) are UAs and thus undertake both collecting and disposal activities.

The data on recycling rates for individual authorities are available from 1998/99 to 2008/09 but only a partial record on recycling rates is available in 2004/05 due to an adjustment to a change in a municipal waste statistics database to a web-based system, WasteDateFlow since 2004. This reporting system aims to help standardise and simplify data capture and at the same time to provide the evidence for meeting EU and national standards and targets and to monitor the performance of authorities under the LATS.  Due to incomplete data for 2004/05, the dataset is naturally divided into before and after 2004/05; the first period is from 1998/99 to 2003/04 and the second period is from 2005/06 to 2008/2009. However, such a division of the period enables us to explore distinct features of two different policy regimes before and after 2005 when the Government starts implementing more intensive use of market-based instruments, such as the Landfill Tax Escalator scheme and the LATS.

The response to the questionnaire ranges from 95% to 100% for the period chosen. For

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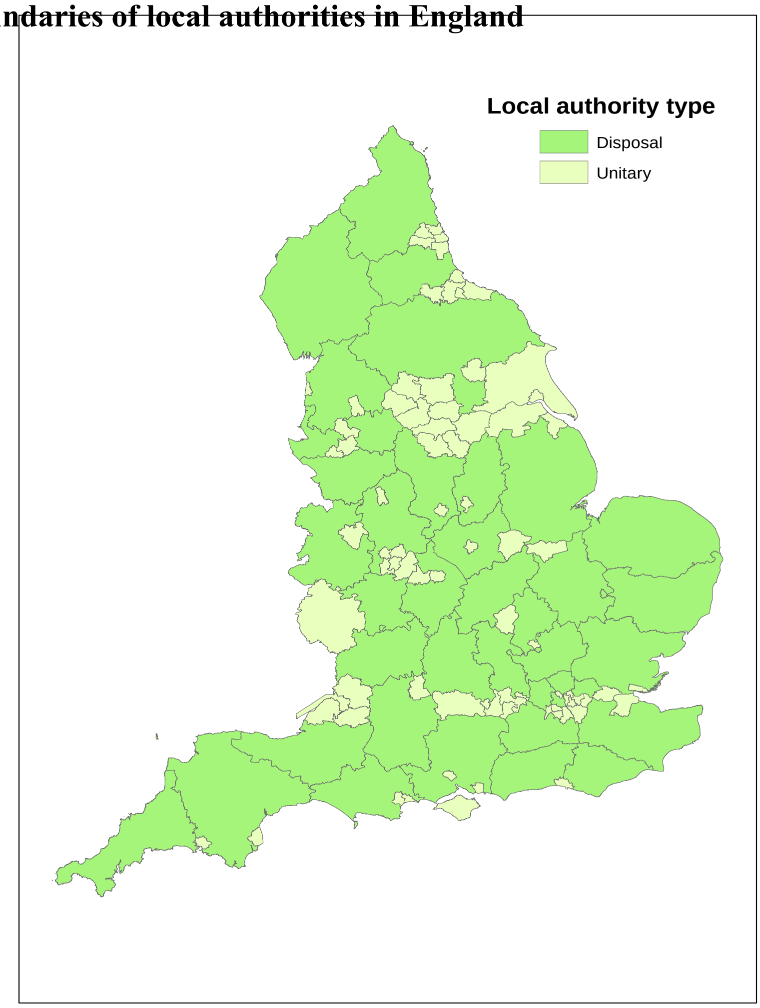
subtract this from the household waste data.

missing values, the average rate of the cross section is used. Since the recycling rates of WDAs include household waste collected for recycling by the WCAs, the current study utilises the recycling rates only at WDA and UA level to avoid double-counting. The total cross section of WDAs and UAs is 120 local authorities. The Isles of Scilly is excluded for consistency with the latter spatial data analysis.[36]

**Figure 2.6: Boundaries of local authorities in England**




For the spatial data analysis, the map data on the local authority boundaries is attained from UKBORDERS[37] which provides digitised boundary datasets for the UK. For this study,

[36] Defining neighbours of the Isles of Scilly is far more limited than other local authorities and thus this observation is excluded in constructing spatial weight matrices and the following analysis on spatial autocorrelation and spatial regressions.

[37] UKBORDERS (http://edina.ac.uk/ukborders) provides various types of boundary datasets (administrative, census, electoral and environmental boundaries etc.).

district-level boundary data from the 2001 Census Boundary Derived Datasets are used.[38] Since the district-level geographical data are based on WCAs and UAs, the original data are edited to create a new map at the WDA and UA level by merging WCAs into their upper-tier WDAs, as shown in Figure 2.6 where WDAs are in green and UAs are in light green.

**Figure 2.7: Distribution of recycling rates in England**

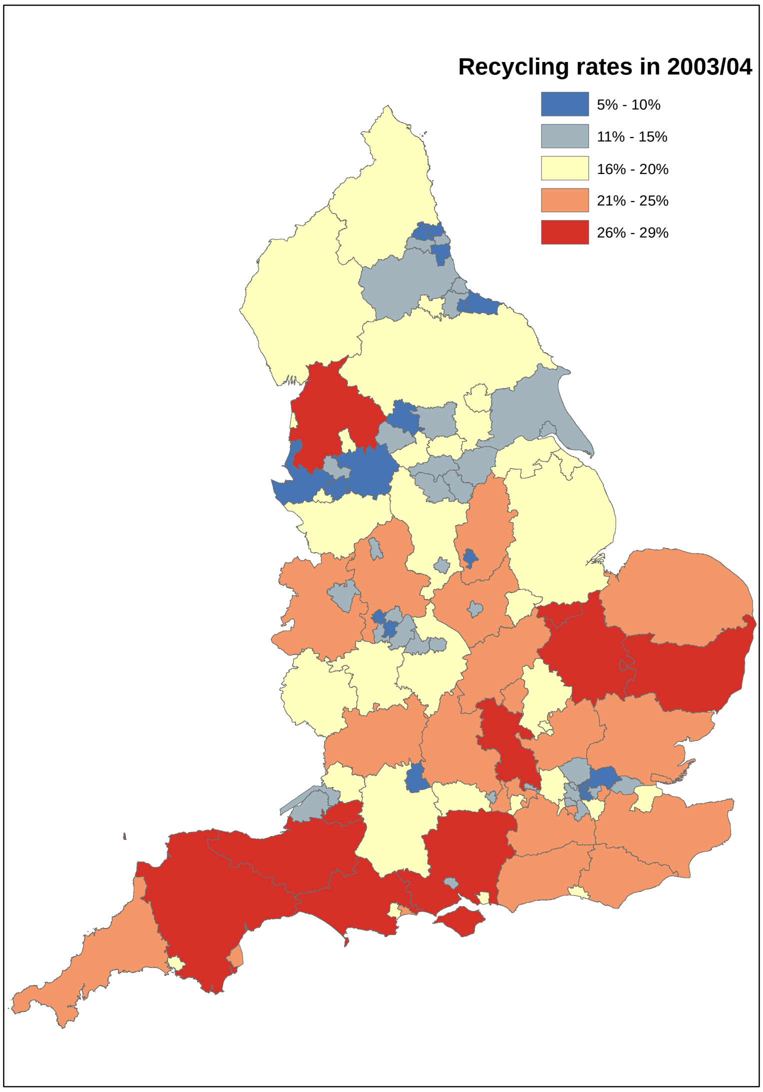



Figure 2.7 displays recycling rates across 120 local authorities in 2003/04. As can be seen, there is a considerable difference in recycling performances across areas. Moreover, we can

[38] This data includes 354 local authorities, made up of metropolitan counties, London boroughs, non-metropolitan districts and unitary authorities. Some of London boroughs are UAs while the rest of London boroughs and all metropolitan boroughs are WDAs. However, non-metropolitan districts are WCAs as subdivisions of metropolitan boroughs in the two-tier structure of local government.

observe some patterns of spatial clustering with high or low values of recycling. For example, relatively high levels of recycling, expressed in red and orange colour are rather concentrated in the south, particularly, the Southwest region whilst a large proportion of the low levels expressed in blue are located in the upper middle or north area.

Given this picture of the distribution of recycling rates across local authorities, the presence of spatial autocorrelation and its change over time appears worthy of further scrutiny. Therefore, in addition to the analysis on the overall improvement of recycling performance and its pattern of progress over the period, the study will further explore the spatially dependent performance in recycling activities and the impact of such spatial interaction has on convergence or divergence of recycling in the latter section.

Household recycling contains materials sent for recycling, composting or reuse by local authorities as well as those collected from household sources by 'private/voluntary' organisations. The recycled materials include paper/card, glass, compostable waste[39] and scrap metal/white goods etc. Among these, paper and card take the largest proportion but in recent years, there has been rapid growth in recycling compostable waste which is as common as paper and card, taking 30% of the total material recycled in 2003/04. Glass and scrap metal/white goods are the next commonly recycled materials. 72% of these materials are collected via bring and drop off and civic collections sites, and the rest (25%) through the kerbside collection service in 1998/99 (DEFRA, 2000). However, the coverage of kerbside collection services has rapidly increased to 40% in 2003/04.

Table 2.3 provides the descriptive statistics of recycling rates in each year. Although the mean value of recycling rates doubles from around 9% to 17% during the first period

[39] Compostable waste includes organic materials (kitchen and garden waste) collected for centralised composting schemes from households. Home composting is not included (DEFRA, 2005).

(1998/99-2003/04), the second period (2005/06-2008/09) exhibits a more rapid growth in the mean by nearly 11% in only 3 years. The comparison of standard deviation between the two periods shows that the second period in general has a high variability in distribution.

**Table 2.3: Descriptive statistics of recycling rates (%)**

| Year | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| 1998 | 8.775 | 5.050 | 1 | 31 |
| 1999 | 9.775 | 5.518 | 1 | 27 |
| 2000 | 10.873 | 5.782 | 1 | 27 |
| 2001 | 11.975 | 5.669 | 1 | 27 |
| 2002 | 13.583 | 5.736 | 1 | 27 |
| 2003 | 16.867 | 5.873 | 5 | 29 |
| 2005 | 25.246 | 7.309 | 9.02 | 42.24 |
| 2006 | 29.533 | 7.374 | 11.75 | 48.5 |
| 2007 | 33.046 | 7.575 | 13.04 | 50.9 |
| 2008 | 36.113 | 7.900 | 19.33 | 52.94 |

The data set also includes explanatory variables which might affect beta convergence. Economic and socio-demographic variables are selected based on the review of literature on the determinants of recycling participation: the average annual earnings per capita, population density, the proportion of women population, the proportion of population with higher education, the proportion of the unemployed and the proportion of population aged over 50.

Data on all these socio-economic and demographic variables are obtained from the national census produced by the Office of National Statistics (ONS). Earnings data are obtained from the Annual Survey of Hours and Earnings (ASHE) while data for the rest of variables are collected from the Nomis,[40] the most detailed and up-to-date UK labour market statistics. The proportion of unemployment is measured based on International Labour Organization (ILO)

[40] Census results are freely available through Nomis (http://www.nomisweb.co.uk), a service provided by the Office for National Statistics (ONS).

approach.[41] As suggested in Strazicich and List (2003), the midpoint year is chosen for the observations of explanatory variables. Thus, 2001 and 2006 are selected for the first and second period respectively in the analysis of beta convergence. Table 2.4 summarises the descriptive statistics of these explanatory variables. The variable for education is the proportion of working age population with NVG level 4 (first degree or equivalents) or above.[42]

**Table 2.4: Descriptive statistics of explanatory variables**

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| 2001 | | | | |
| Earnings (£) | 19,293.63 | 5,992.871 | 13,052 | 60,451 |
| Density(people per km$^2$) | 1,767.679 | 2,018.607 | 60.531 | 9,526.89 |
| Women | 0.512 | 0.032 | 0.459 | 0.741 |
| Education | 0.226 | 0.072 | 0.069 | 0.484 |
| Unemployed | 0.05 | 0.026 | 0† | 0.120 |
| Ageover50 | 0.322 | 0.051 | 0.165 | 0.456 |
| 2006 | | | | |
| Earnings (£) | 23,623.46 | 7,669.8 | 17,372 | 81,844 |
| Density(people per km$^2$) | 1,813.983 | 2,111.727 | 61.023 | 10,526.57 |
| Women | 0.517 | 0.018 | 0.461 | 0.57 |
| Education | 0.262 | 0.093 | 0.124 | 0.855 |
| Unemployed | 0.055 | 0.025 | 0† | 0.131 |
| Ageover50 | 0.328 | 0.064 | 0.161 | 0.693 |

*Notes*: †In 2001, Rutland County Council and City of London had zero unemployment rate while North Somerset Council and City of London in 2006. All of them are unitary authorities.

Table 2.5 and Table 2.6 display the correlation matrix between explanatory variables in 2001 and 2006 respectively. It appears that the correlation is not particularly high except the one between education and earnings. Overall, there are moderate levels of correlation among

[41] The ILO approach is based on a survey and thus subject to sampling error. Moreover, this does not distinguish between those who work full time and those who work part time. (e.g. anyone who works only one hour's paid work is also considered as employed).

[42] Appendix 2.5 shows the Educational Qualifications and their NVQ equivalents.

some variables. Density and earnings are positively correlated at around 0.46 in both years. The correlation between density and the proportion of the unemployed is at 0.43 and 0.59 in 2001 and 2006 respectively. On the other hand, the density is negatively correlated with the proportion of population aged over 50 at around 0.51 and 0.56 in respective years. As expected, there is a negative correlation between the proportion of population with high educational levels and local authorities' unemployment.

**Table 2.5: Correlation between explanatory variables in 2001**

| **2001** | Earning | Density | Women | Education | Unemployed | Ageover50 |
|---|---|---|---|---|---|---|
| Earning | 1 | | | | | |
| Density | 0.466 | 1 | | | | |
| Women | 0.369 | 0.088 | 1 | | | |
| Education | 0.568 | 0.263 | 0.339 | 1 | | |
| Unemployed | -0.065 | 0.427 | -0.123 | -0.325 | 1 | |
| Ageover50 | -0.218 | -0.508 | 0.176 | -0.011 | -0.44 | 1 |

**Table 2.6: Correlation between explanatory variables in 2006**

| **2006** | **Earning** | **Density** | **Women** | **Education** | **Unemployed** | **Ageover50** |
|---|---|---|---|---|---|---|
| Earning | 1 | | | | | |
| Density | 0.459 | 1 | | | | |
| Women | -0.113 | -0.115 | 1 | | | |
| Education | 0.704 | 0.216 | -0.072 | 1 | | |
| Unemployed | -0.012 | 0.59 | -0.022 | -0.32 | 1 | |
| Ageover50 | 0.062 | -0.562 | 0.155 | 0.15 | -0.528 | 1 |

## 2.6 Sigma Convergence

A downward trend in dispersion is viewed as evidence of declining cross-sectional dispersion. In addition to standard deviation in Table 2.4, sample variance, $s^2$ is calculated as an indicator of sigma convergence:

$$s^2 = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}[\ln(\text{Recycling}_i) - \ln(\overline{\text{Recycling}})]^2} \quad \textbf{(2.17)}$$

where $\ln(\overline{\text{Recycling}})$ is the mean or expected value of logged recycling rate and $n$ is the number of observations. Alternatively, the average absolute deviation (AAD), the median absolute deviation (MAD) and interquartile range (IQR) are also computed as a measure of the cross-sectional dispersion. The AAD is the average value of the absolute difference between the variable and the mean:

$$AAD = \frac{\sum_{i=1}^{n}[\left| \ln(\text{Recycling}_i) - \ln(\overline{\text{Recycling}}) \right|]}{n} \quad \textbf{(2.18)}$$

The MAD is defined as:

$$MAD = median_i \left| \ln(\text{Recycling}_i) - \ln(\widetilde{\text{Recycling}}) \right| \quad \textbf{(2.19)}$$

where $\ln(\widetilde{\text{Recycling}})$ is the median value of ln(Recycling$_i$). Both measures are more resilient to outliers of a dataset because they are not squared. The sample variance gives greater weights to large deviations as the differences from the mean are squared. The IQR is equal to the difference between the third and first quartiles: $IQR = Q_3 - Q_1$. Thus it measures the dispersion of the middle fifty and does not consider tail behaviour.

Figure 2.8 and 2.9 display these measures of sigma convergence of recycling rates during the first (1998/99-2003/04) and second (2005/06-2008/09) respectively. As can be seen, there is an increase in dispersion in early years but generally the dispersion parameters show a downward trend which implies that recycling rates converge over time.

**Figure 2.8: Measures of sigma convergence 1998/99-2003/04**

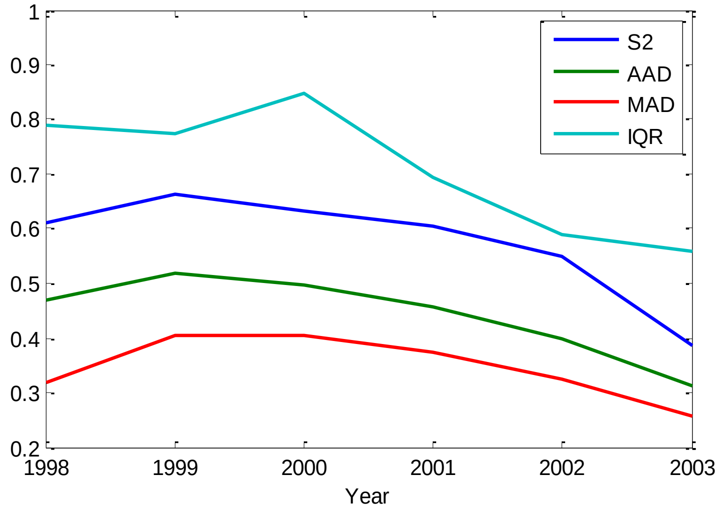
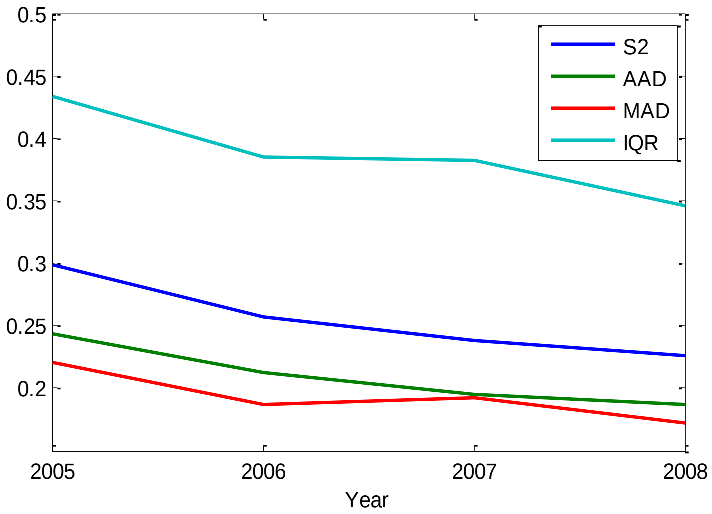



**Figure 2.9: Measures of sigma convergence 2005/06-2008/09**




## 2.7 Beta Convergence

The conventional beta convergence regression is tested with and without a vector of explanatory variables, *Z*, which includes the average earnings, population density, the unemployment rate, the proportion of people having attained a higher educational level, and women and population over 50 years old. The conventional $\beta$ convergence regression is:

$$\frac{1}{T}\ln(\text{Recycling}_{it} - \text{Recycling}_{i0}) = \alpha + \beta \ln(\text{Recycling}_{i0}) + \gamma Z_i + e_i \qquad \textbf{(2. 20)}$$

Recycling $_{i0}$ is the recycling rate of local authority *i* at the initial year and *T* is the difference between the initial year and the final year. The dependent variable is the average growth rate for *T* years, calculated as a change in the log of recycling rates from the initial year to the final year. In the presence of beta convergence, the growth rate and the initial performance are expected to have a negative relationship, and hence a negative value of $\beta$. The equation (2.20) without a vector *Z* tests unconditional convergence. However, once differences in Z are accounted for, local authorities are allowed to reach their own steady states depending on Z and thus the equation tests conditional convergence. Based on the previous literature on determinants of recycling participation, I hypothesise as follows.

Firstly, the level of income is generally considered to have a positive relation with recycling rates if recycling has the characteristic of a luxury good. However, the opposite effect might also be expected due to rising opportunity cost of time associated with higher incomes. Secondly, unemployed people may have a lower opportunity cost of spending time on recycling. Thus, there may be a positive relationship between unemployment rates and recycling rates (Hage and Söderholm, 2008). However, both unemployment and income also capture the degree of social deprivation within a local authority. It could be argued that an authority with several social problems is less likely to have the resources or perhaps commitment to devote to 'less essential' activities such as recycling. This suggests that income is positively related to recycling while unemployment is negatively related.

Thirdly, population density is also expected to have ambiguous effects on recycling rates insofar as it impacts on the availability of land for landfill and the type of housing stock (determining the personal costs of recycling). Fourthly, women are generally believed to be more concerned with environmental problems and thus a greater proportion of women may have a positive effect on recycling rates. Finally, the proportion of population with higher education and of the older population are also expected to have positive effects on recycling rates as those people are more likely to act in an environmentally conscious manner.

Table 2.7 shows the OLS estimates of the cross-sectional beta convergence regression for the first period (1998/99-2003/04). The analysis is conducted by adding explanatory variables one at a time. In all regression specifications, the presence of convergence is strongly supported with a negative coefficient on the logged initial recycling rate, ranging from -0.11 to about -0.13. The presence of convergence means that local authorities with initially low recycling rates tend to improve their recycling performance faster than those with initially high rates. The implied rate of convergence ranges from 16.7% to 21.1% which in turn means a half life of deviation from ones' steady state of recycling rates ranging from 3.27 to 4.13 years. In other words, it takes about 3 or 4 years to eliminate a half gap between the initial rate and the steady state.[43]

Of explanatory variables which are expected to determine the steady-state recycling rate, most of them are statistically insignificant except for population density and unemployment. However, the F statistics testing the joint significance of the parameters on potential determinants of the steady state confirm the presence of conditional convergence. The first regression shows the presence of unconditional convergence. In the second regression, earnings are statistically significant at the 5% significance level. However, as can be seen in later regressions, it becomes statistically insignificant once omitted variables, such as population density, are included in the regression.

[43] Refer back to page 44-45 for the formulas of speed of convergence and the half-life.

In the third regression, the inclusion of population density improves the overall fit and is statistically significant at the 1% significance level in all regressions. This implies that local authorities approach their own steady-state level of recycling determined by population density. A negative sign on density means that densely populated local authorities move slowly towards a lower rate of recycling than sparsely populated authority. The interpretation may be related to big city effects. Residents in highly populated areas are likely to have greater opportunity costs of recycling activities in time, space and money and thus will choose a cheaper way of managing their waste, such as simple waste disposal. Furthermore, they are likely to feel less social pressure to recycle as their recycling behaviour is less visible than villagers' recycling.

In the fifth regression, the proportion of population with higher education (first degree and above) is only weakly significant statistically and negatively related to the growth rate of recycling rate. While its sign is unexpected, a positive correlation coefficient at around 0.56 between earnings and higher educational level implies that a higher opportunity cost might be captured by the variable for high level of educational attainment.

In the sixth regression, the proportion of the unemployed is highly significant statistically. This suggests that local authorities with high unemployment may be under more pressure to cope with stress due to poverty or other problems associated with unemployment such as crime. Thus environmental issues will be placed in a lower priority and less resource will be allocated by local authorities to recycling activities. Neither the proportion of women population nor the proportion of population aged over 50 is statistically significant. The overall fit of all the specifications is relatively high with an adjusted $R^2$ ranging from 0.60 to 0.77. With the inclusion of explanatory variables, the magnitude of coefficient ($\beta$) on the initial recycling rate becomes slightly higher. The bigger the absolute value of $\beta$ is, the faster the speed of convergence in a given time period.

The Jarque-Bera test indicates that the null hypothesis of a normal error is rejected in all cases. In this case, other diagnostic tests should be interpreted carefully since normality is an underlying assumption of the tests for heteroscedasticity. While there is a moderate level of multicollinearity, the results of Breusch-Pagan test and Ramsey Reset test show both the null of homogeneity and the null of linear specification cannot be rejected.

Table 2.8 displays the results of beta convergence regressions for the second period (2005/06-2008/09). The results also confirm the presence of convergence. Although it appears that only population density is statistically significant, the F statistics for the joint significance of the long-run determinants are all statistically significant implying that each local authority moves towards their own long-run equilibrium. As in the first period, density is negatively related to the growth and the steady-state of recycling rates which again indicates difficulties in increasing recycling participation in densely populated areas. The speed of convergence ranges from 0.093 to 0.134 which implies a half-life between 5.15 and 7.42 years. Therefore it takes longer to reach to the steady state of each local authority in the second period compared to the first period. Below we will argue that this may be a consequence of the regulatory policy instruments adopted in the second time period.

From the results of diagnostic tests, the null of normality is not rejected but the presence of heteroscedasticity is detected. To deal with the concerns about failure to meet classical assumptions pertaining to the residuals, such as lack of normality and heteroscedasticity, the robust standard errors using the Huber-White sandwich estimators are utilised. The results are provided in Appendix 2.7. The estimates of the coefficients are exactly the same as in the OLS regressions but statistical significance changes. For example, higher education in the first period becomes more significant. The robust estimates for the second period show that population density is significant only at the 10% significance level. However, the F statistics for conditional convergence are statistically significant across all regressions, implying the presence of conditional convergence in both periods.

The high correlation found between the growth rate and initial level may arise due to the underlying calculation of the growth rate. That is, the initial level appears on both sides of the beta convergence regression. One way to deal with this problem is to use an earlier lag of the log of income as instruments (Barro and Sala-i-Martin, 2004, p.472). Appendix 2.8 diplays the results of instrumental variable (IV) estimations for both periods. All specifications still confirm the presence of convergence in a conditional sense for the first period but in an unconditional sense for the second period.

Appendix 2.9 shows the results of beta convergence for the combined dataset over the whole period. There is strong evidence of conditional convergence in OLS but IV estimations. Population density is still the only long-run determinant with statistical significance in the results of both estimation methods. The half-year ranges from 3.69 to 4.11 years which is about the same with the results of the first period.

**Table 2.7: Estimation results of the beta convergence model 1998/99-2003/04**

**OLS**
**Total observation: 120 cross-section data from 1998/99 to 2003/04**
**Dependent variable: growth rate of recycling rate (log difference of recycling rate between 2003/04 and 1998/99)**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| **Constant** | 0.3777*** | 0.7500*** | 0.6244*** | 0.6039*** | 0.5320*** | 0.5910*** | 0.5109*** |
| **ln(Recycling1998)** | -0.1134*** | -0.1141*** | -0.1245*** | -0.1238*** | -0.1216*** | -0.1304*** | -0.1298*** |
| **ln(Earning)** | | -0.0375*** | -0.0048 | -0.0066 | -0.0000 | -0.0006 | 0.0043 |
| **ln(Density)** | | | -0.0260*** | -0.0258*** | -0.0261*** | -0.0209*** | -0.0196*** |
| **Women** | | | | 0.0687 | 0.1111 | 0.0580 | 0.0155 |
| **Education** | | | | | -0.0761 | -0.1303* | -0.1310* |
| **Unemployed** | | | | | | -0.6327*** | -0.5587** |
| **Ageover50** | | | | | | | 0.1231 |
| **$R^2$** | 0.6024 | 0.6309 | 0.7433 | 0.7439 | 0.7462 | 0.7650 | 0.7678 |
| **Adjusted $R^2$** | 0.5990 | 0.6246 | 0.7367 | 0.7350 | 0.7351 | 0.7526 | 0.7533 |
| **AIC** | -346.7506 | -353.6815 | -395.2893 | -393.5481 | -392.6504 | -399.8868 | -399.3059 |
| **Speed of convergence** | 0.1674 | 0.1690 | 0.1948 | 0.1930 | 0.1873 | 0.2111 | 0.2094 |
| **F statistic for conditional convergence** | | 9.04*** | 31.86*** | 21.19*** | 16.16*** | 15.65*** | 13.30*** |
| **Jarque-Bera** | 23.39*** | 24.12*** | 49.75*** | 49.31*** | 46.04*** | 42.86*** | 40.48*** |
| **Multicollinearity** | 0.39763776 | 0.36911841 | 0.25665147 | 0.25609847 | 0.25375682 | 0.23495801 | 0.23219578 |
| **Breusch-Pagan** | 1.51 | 0.73 | 0.16 | 0.23 | 0.34 | 1.79 | 2.84* |
| **Ramsey RESET** | 0.41 | 1.60 | 0.75 | 0.65 | 0.69 | 0.31 | 0.21 |

*Notes*: Standard errors are in parentheses. Significance is indicated by *, **, *** for 0.1, 0.05 and 0.001 level, respectively. The speed of convergence is computed by $\lambda = -[(1/T)\ln(T\beta + 1)]$. F statistic tests the (joint) significant of a vector $Z$ estimated in each regression. Jarque-Bera (JB) is a test for normality. The null is normally distributed error terms. Multicollinearity is examined using the Variance Inflation Factors (VIFs). The 1/VIF is the Tolerance which ranges from 0.0 to 1.0, with 1.0 being the absence of multicollinearity. Breusch-Pagan tests the null hypothesis that the error variances are all equal versus the alternative that the error variances are a multiplicative function of one or more variables. The Ramsey Regression Equation Specification Error Test (RESET) test (Ramsey, 1969) is a general specification test for the linear regression model, testing whether non-linear combinations of the explanatory variables have any power in explaining the exogenous variable. If non-linear combinations of the estimated values are statistically significant, the linear model is misspecified.

### Table 2.8: Estimation results of the beta convergence model 2005/06-2008/09

**OLS**
**Total observation: 120 cross-section data from 2005/06 to 2008/09**
**Dependent variable: growth rate of recycling rate (log difference of recycling rate between 2008/09 and 2005/06)**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| **Constant** | 0.5214*** | 0.7309*** | 0.7985*** | 0.8790*** | 0.9198*** | 0.9018*** | 0.8923*** |
| **ln(Recycling2005)** | -0.1243*** | -0.1296*** | -0.1604*** | -0.1616*** | -0.1625*** | -0.1628*** | -0.1628*** |
| **ln(Earning)** | | -0.0191* | -0.0075 | -0.0080 | -0.0132 | -0.0114 | -0.0110 |
| **ln(Density)** | | | -0.0126*** | -0.0129*** | -0.0126*** | -0.0099** | -0.0095** |
| **Women** | | | | -0.1358 | -0.1317 | -0.1259 | -0.1371 |
| **Education** | | | | | 0.0398 | 0.0122 | 0.0100 |
| **Unemployed** | | | | | | -0.2491 | -0.2281 |
| **Ageover50** | | | | | | | 0.0268 |
| | | | | | | | |
| **$R^2$** | 0.4342 | 0.4521 | 0.4950 | 0.4969 | 0.5000 | 0.5063 | 0.5069 |
| **Adjusted $R^2$** | 0.4295 | 0.4427 | 0.4819 | 0.4794 | 0.4780 | 0.4801 | 0.4760 |
| **AIC** | -415.4676 | -417.3117 | -425.0997 | -423.5520 | -422.2873 | -421.8076 | -419.9529 |
| **Speed of convergence** | 0.0933 | 0.0984 | 0.1312 | 0.1326 | 0.1337 | 0.1340 | 0.1340 |
| **F statistic for conditional convergence** | | 3.81* | 6.98*** | 4.77*** | 3.75*** | 3.30*** | 2.75** |
| **Jarque-Bera** | 4.563 | 4.277 | 4.442 | 4.921* | 4.133 | 4.626* | 5.038 |
| **Multicollinearity** | 0.56575101 | 0.54791481 | 0.50499738 | 0.50309741 | 0.50002445 | 0.49372946 | 0.49313179 |
| **Breusch-Pagan** | 6.09** | 6.17** | 6.04** | 5.61** | 5.59** | 5.63** | 5.35** |
| **Ramsey RESET** | 0.05 | 0.09 | 0.19 | 0.15 | 0.18 | 0.19 | 0.18 |

*Notes*: See notes for Table 2.7.

## 2.8 Distribution Dynamics

Two commonly adopted nonparametric methods proposed by Quah (1993a, 1993b, 1996, 1997) are employed to analyse the inter- and intra-distribution dynamics of recycling rates: kernel density estimates and stochastic kernel estimates. As summarised in the review of the pollution convergence literature, a kernel density approach shows shape dynamics of the distribution and more importantly, stochastic kernels provide information on mobility dynamics in the distribution which might not be fully uncovered in the analysis of beta and sigma convergence.

Following the procedures commonly adopted in the distribution dynamics literature, recycling rates in relative terms are used since normalisation to the cross-section average allows us to distinguish local authority-specific movement from common trends.

$$RR_{it} = (\mathrm{Recycling}_{it} / \overline{\mathrm{Recycling}}_t) \qquad \textbf{(2.21)}$$

where $\overline{\mathrm{Recycling}}_t$ is the average of recycling levels for the entire cross section at time *t*. The average relative recycling rate is assigned a value of 1.

Firstly, the annual kernel densities of relative recycling rates are plotted in Figure 2.10 for the first period (1998/00-2003/04) and in Figure 2.11 for the second period (2005/06-2008/09). The probability density function $f(\cdot)$ of relative recycling rates is estimated based on a Gaussian kernel function:

$$f_t(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \qquad \text{where} \quad K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2} \qquad \textbf{(2.22)}$$

where $x_i$ is relative recycling rates of local authority $i$ , $n$ is the number of observations and $h$ is the bandwidth of the kernel-smoothing window. The smoothing parameter, $h$ must decrease with increasing $n$ as it controls how widely spread the probability mass is around a point as well as how smooth or rough the density estimates are. Here, $h$ is calculated by a function of the number of points in $x$. This bandwidth may be too big to reveal features like multiple modes and thus is optimal only for estimating normal densities. Therefore, as an alternative to a smooth probability density function, histograms of relative recycling rates for each year are also used to show the probability distribution of relative recycling (Figure 2.12). For completeness of the distributional analysis over time, boxplots of relative rates are also displayed in Figure 2.13.

Graphical representations of the annual kernel densities show how the shape of distribution evolves over the period. The following interesting features emerge from Figure 2.10 and 11. Firstly, there is in general no multimodality over the whole period. Secondly, local authorities with relative rates of recycling around 1 take the highest proportion of the sample in both periods. Third, there are nonetheless differences between the two periods.

**Figure 2.10: Cross-sectional distribution of relative recycling rates 1998/99-2003/04**

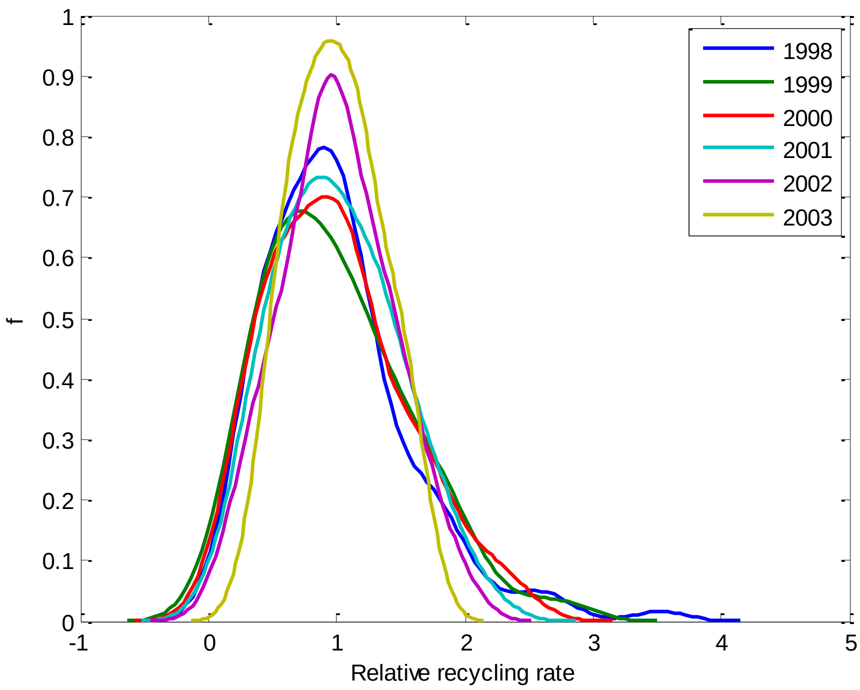
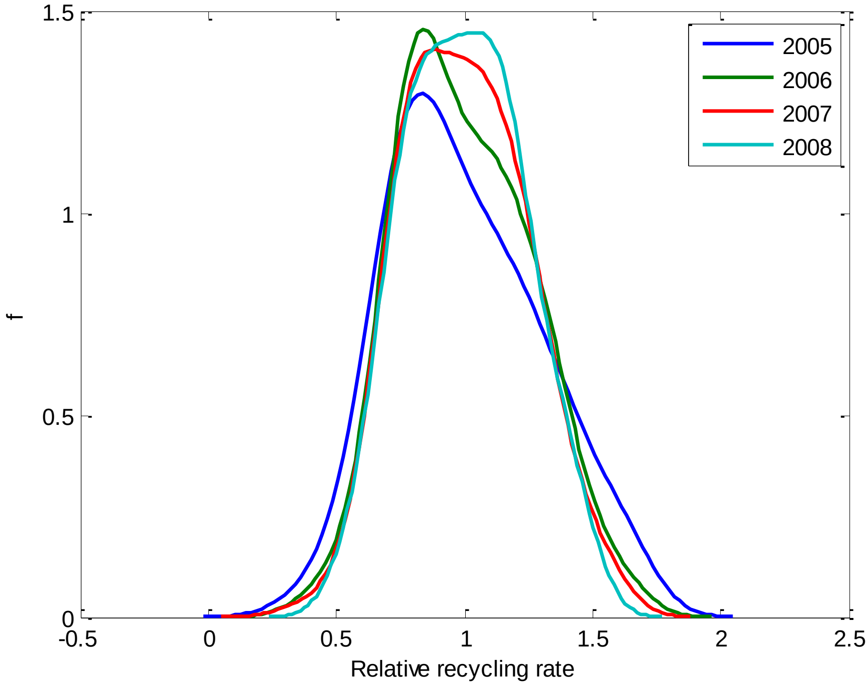


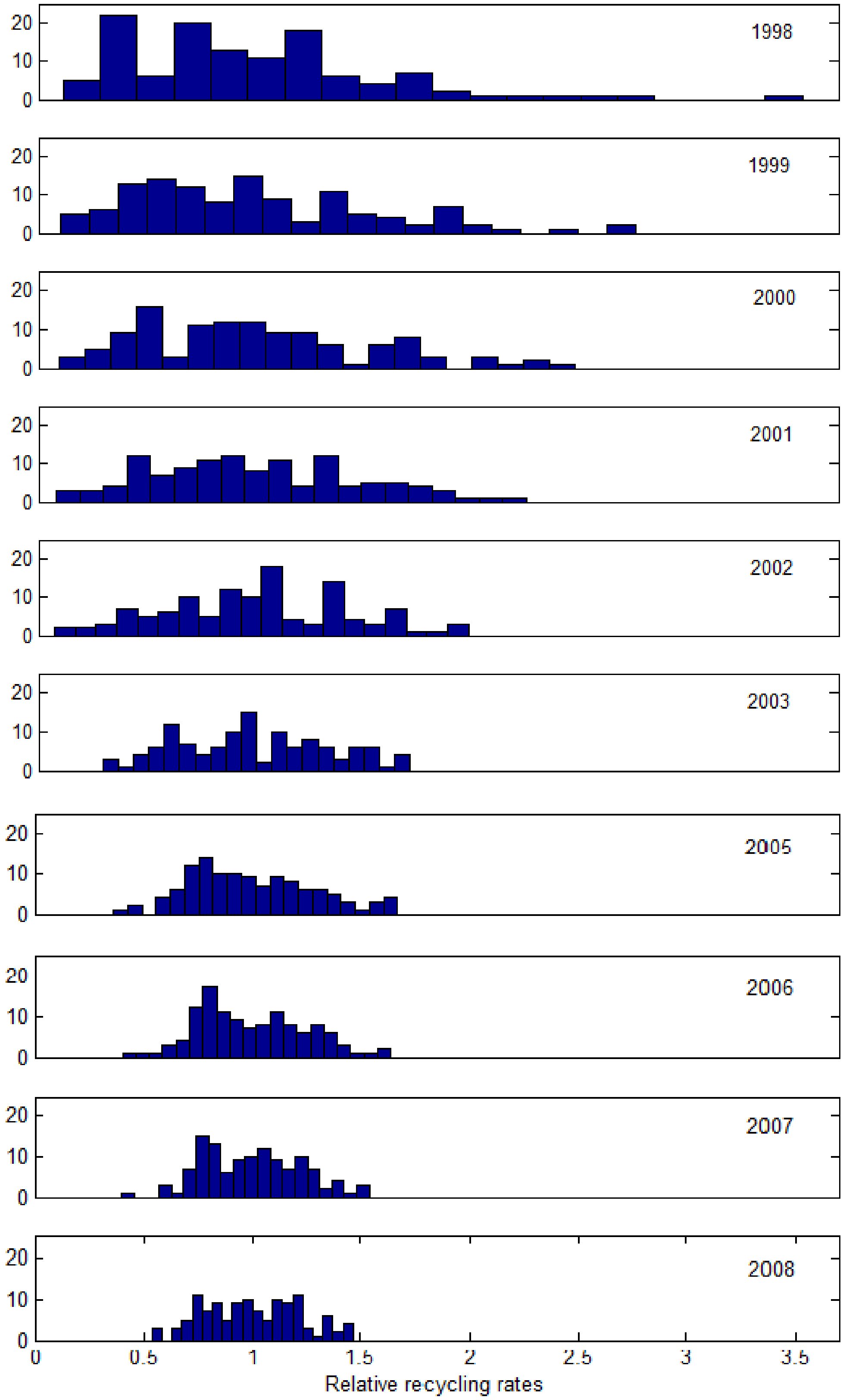
**Figure 2.11: The cross-sectional distribution of relative recycling rates 2005/06-2008/09**




In the first period, the distributions are more spread out, particularly in earlier years, with long upper tails. However, there is a large reduction in the probability mass of higher relative values over the period, which leads to a decrease in the distance between both ends of the distribution. In other words, there is a considerable increase in the probability mass concentrated around the average, enabling us to conclude that there is a global pattern of convergence of recycling rates across local authorities.

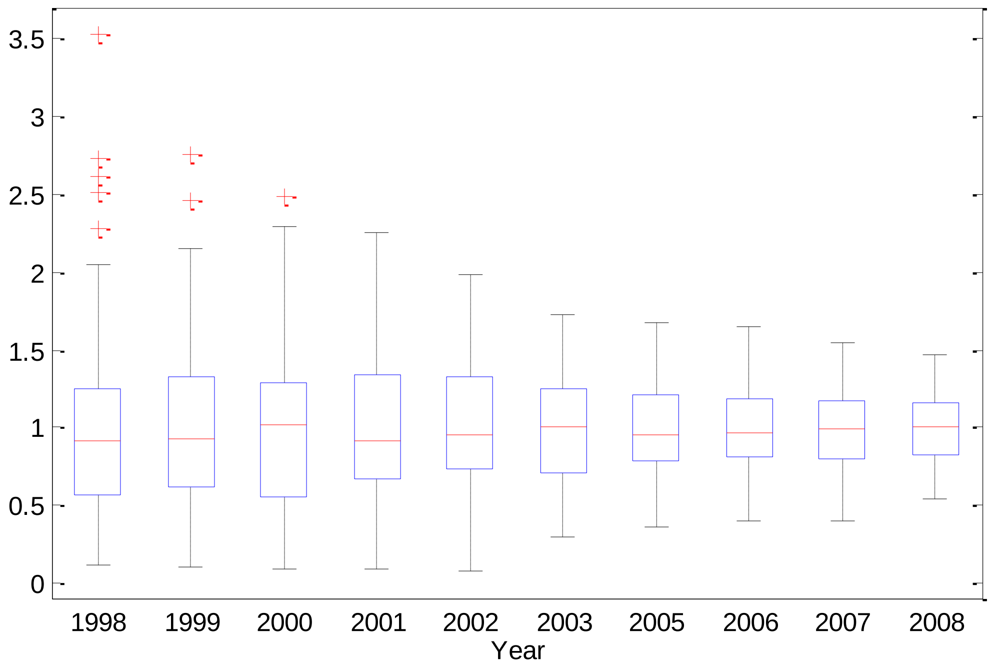
Throughout the second period, there is also a movement in probability mass towards the average as the dispersion decreases and the probability becomes higher around the value 1. However, the kernel density estimates in the second period are initially more symmetric and already concentrated around the average compared to the first period. Therefore, the process of convergence can be said to be less prominent in the second period.

**Figure 2.12: Histograms of relative recycling rates**



Comparing the kernel densities and histograms, we can easily notice a problem of using a large bandwidth in kernel density estimates which leads to over-smoothing. Particularly in early years, several significant peaks observable in the histograms are skipped in the kernel smoothing density estimates. In other words, the presence of multimodality and its tendency to move toward a unimodal distribution are largely ignored. This will in turn overlook another feature of a convergence process. As can be seen in the histograms, multimodality tends to become less significant over the periods, which supports the presence of convergence. Nevertheless, the general trends of converging patterns shown in the kernel densities are also confirmed in the histograms.

**Figure 2.13: Boxplots of relative recycling rates**




In Figure 2.13, the central mark on each box is the median and the edges of the box are the 25th and 75th percentiles. Outliers in red individual markers are more frequently found in the early boxplots. It is clear that all of them are outstanding performers since they are always located in the upper portions. While the medians and the means are not significantly different from each other, the size of the boxes decreases over time, which may imply a pattern of convergence in relative recycling rates across local authorities.

While the above graphical representations are useful to analyse the changes in the shape of distributions over the period and thus to identify inter-distributional characteristics, the analysis of transition dynamics using stochastic kernels can reveal a variety of characteristics of intra-distribution dynamics, for example, persistence, churning or mobility or separating (Quah, 1997, p.29). Persistence occurs when local authorities with high recycling rates at time $t+\tau$ already recycle at relatively higher levels at time $t$ and similarly those with low rates at time $t+\tau$ also recycle at relative low levels at time $t$. Mobility or churning implies that local authorities with high rates and low rates at time $t$ exchange their positions at time $t+\tau$. Separating means the distribution polarising into two or more peaks of high rates and low rates. The last case refers to club convergence where there are two or more stable, steady state equilibria instead of global convergence where there is only one equilibrium to which all local authorities converge.

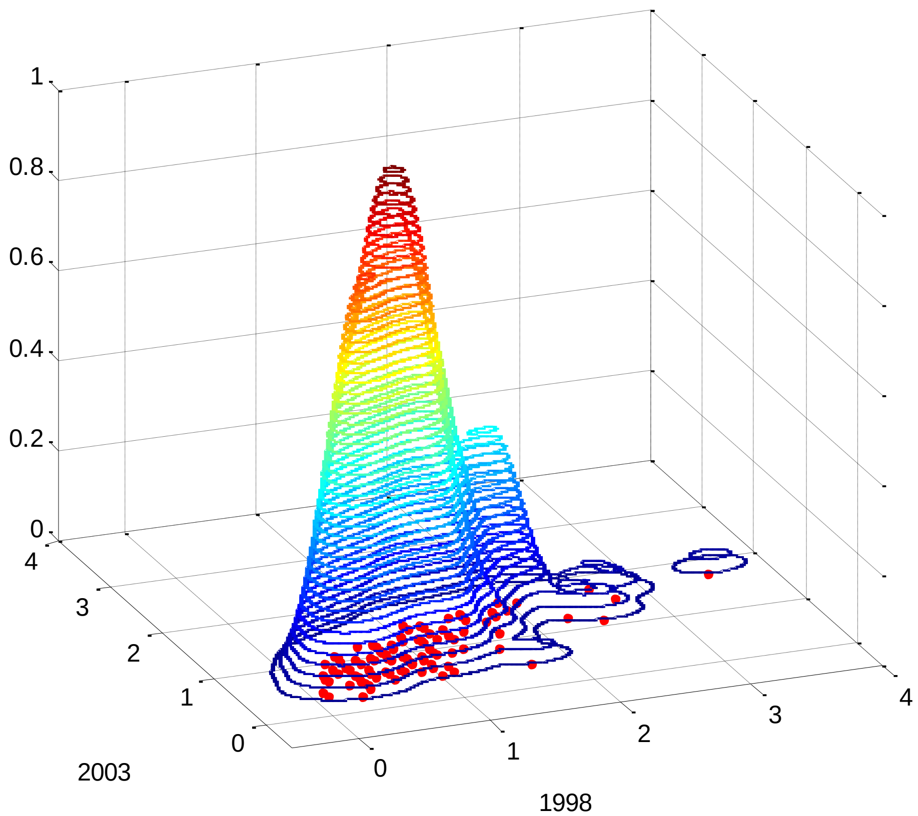
Figure 2.14 plots the surface of the conditional distribution $g_\tau(y \mid x)$ for the first period where $\tau$ is 6-year interval and thus, $y$ is relative recycling rates in 2003/04, $x$ is relative recycling rates in 1998/99, given by:

$$g_\tau(y \mid x) = \frac{f_{t,t+\tau}(y,x)}{f_t(x)} \qquad \textbf{(2.23)}$$

where $f_{t,t+\tau}(y,x) = \frac{1}{h_1 h_2} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h_1}\right) K\left(\frac{y - y_i}{h_2}\right)$ is the joint density of $x$ and $y$. The kernel is assumed to be Gaussian and the two bandwidth parameters are chosen optimally without assuming a parametric model for the data which then allows us to avoid inaccuracy in the estimation of multimodal densities with widely separated modes.[44]

The three-dimensional graph of the stochastic kernel estimate shows how the cross-sectional distribution at the initial year evolves into the distribution observed at the final year. As before, the value 1 indicates those local authorities which perform at the average level across all local authorities, and lower (higher) than 1 indicates those authorities are performing below (above) the average. The average rate of recycling in 1998 and in 2003 is around 8.8% and 16.9% respectively. In the Figure 2.14, we can readily identify a dominant peak in the stochastic kernel.

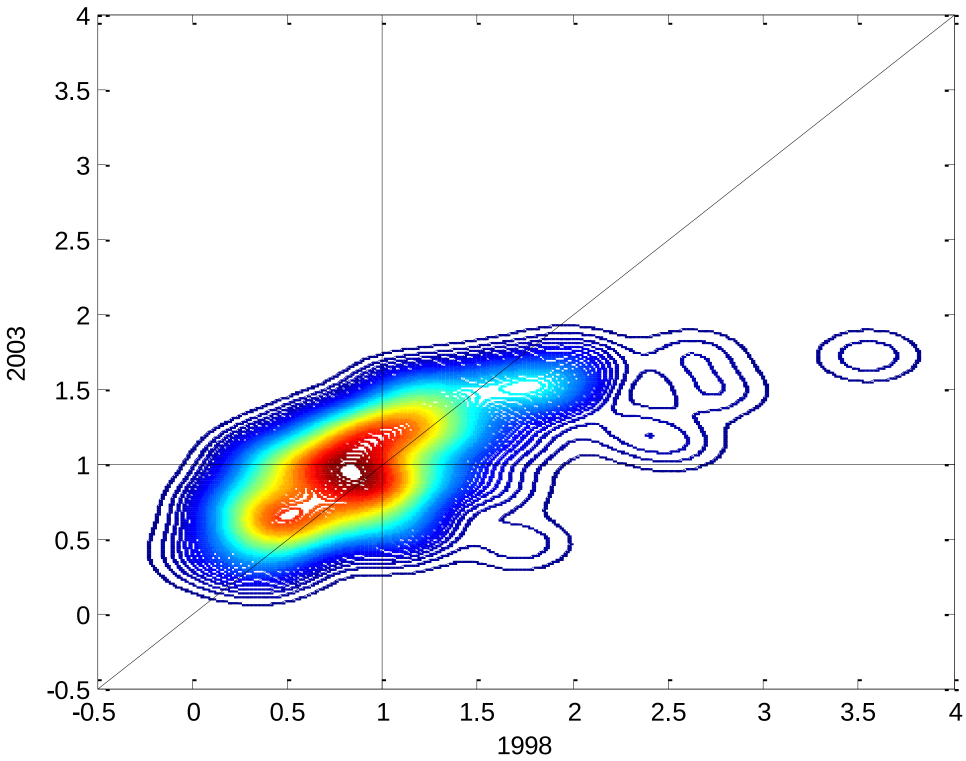
**Figure 2.14: Relative recycling rates dynamics 1998/99-2003/04**




[44] I utilised the bivariate kernel density estimator procedure written in Matlab by Zdravko Botev (2007, updated in 2009), downloadable from http://www.mathworks.com/matlabcentral/fileexchange/17204-kernel-density-estimation. See Botev et al. (2010) for details.

Figure 2.15 presents the contours of the conditional distribution. In the contour plot, a red area corresponds to a large probability mass. The 45-degree line represents the position of local authorities in the distribution which did not change from 1998/99 to 2003/04. If the probability mass is concentrated around the 45-degree line, the intra-distribution dynamics are characterised by a high level of persistence in relative positions of the cross section over time and, therefore, low mobility and lack of convergence. If, on the other hand, the density are located mainly on a line which is rotated clockwise or counter-clockwise from the 45-degree line, this would indicate high mobility of the distribution. An observed clockwise rotation would indicate the presence of convergence as both high and low values move towards the average in the next period. On the other hand, a counter-clockwise rotation would indicate the presence of divergence as high values become even higher and low values become even lower in the next period.

**Figure 2.15: Relative recycling rates dynamics contour plot 1998/99-2003/04**



As can be seen in Figure 2.15, a larger proportion of distribution indicated by the red area is located above the 45-degree line, which implies an improvement in recycling performance across the entire distribution. Such progress in recycling performance is mainly observed in those local authorities with initially low rates of recycling. Although the density is very low, local authorities with initially high rates of relative recycling tend to move towards the average of English local authorities. The overall dynamic distribution is slightly rotated in a clockwise direction relative to the main diagonal. This indicates the presence of convergence but mainly achieved by the high mobility of local authorities with low values. Overall, local authorities converge to equality in recycling rates.

**Figure 2.16: Relative recycling rates dynamics 2005/06-2008/09**

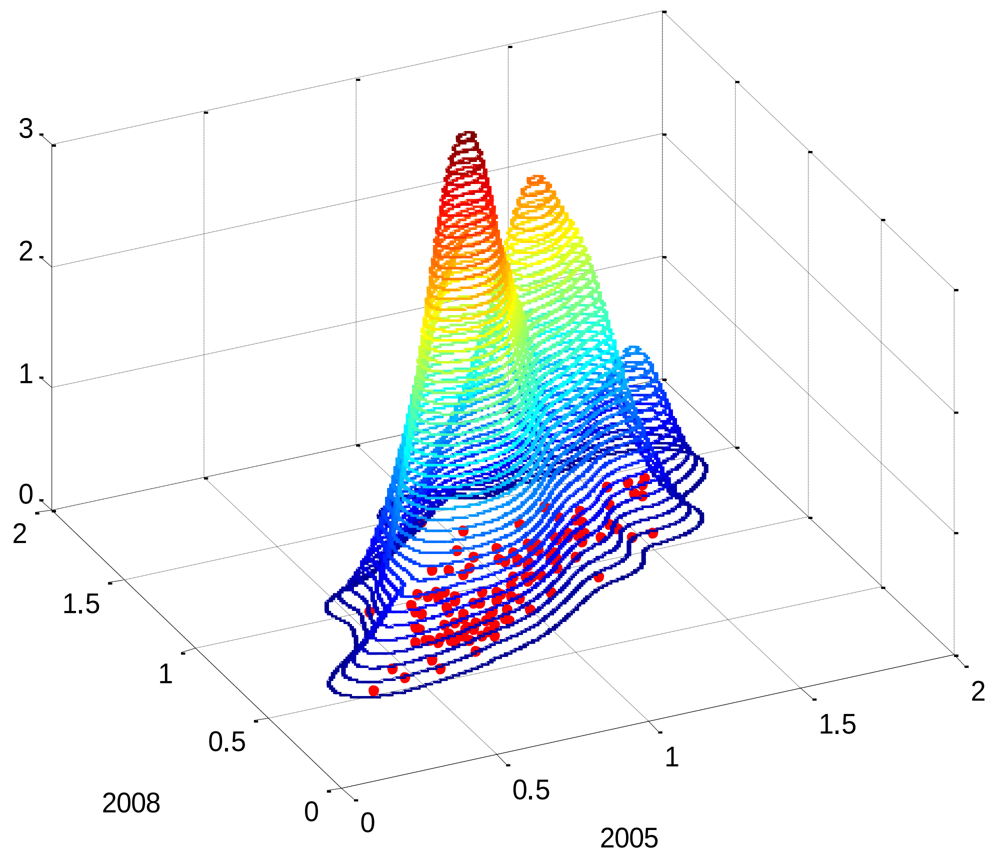


Figure 2.16 plots the surface of the conditional distribution $g_\tau(y\,|\,x)$ for the second period where $\tau$ is 4-year interval and thus, $y$ is relative recycling rates in 2008/09, $x$ is relative recycling rates in 2005/06. The average rate in 2005 and 2008 is around 25.2% and 36.1% respectively. Twin peaks appear while the probability density of clustering between high values is lower than that of clustering between low values.

**Figure 2.17: Relative recycling rates dynamics contour plot 2005/06-2008/09**

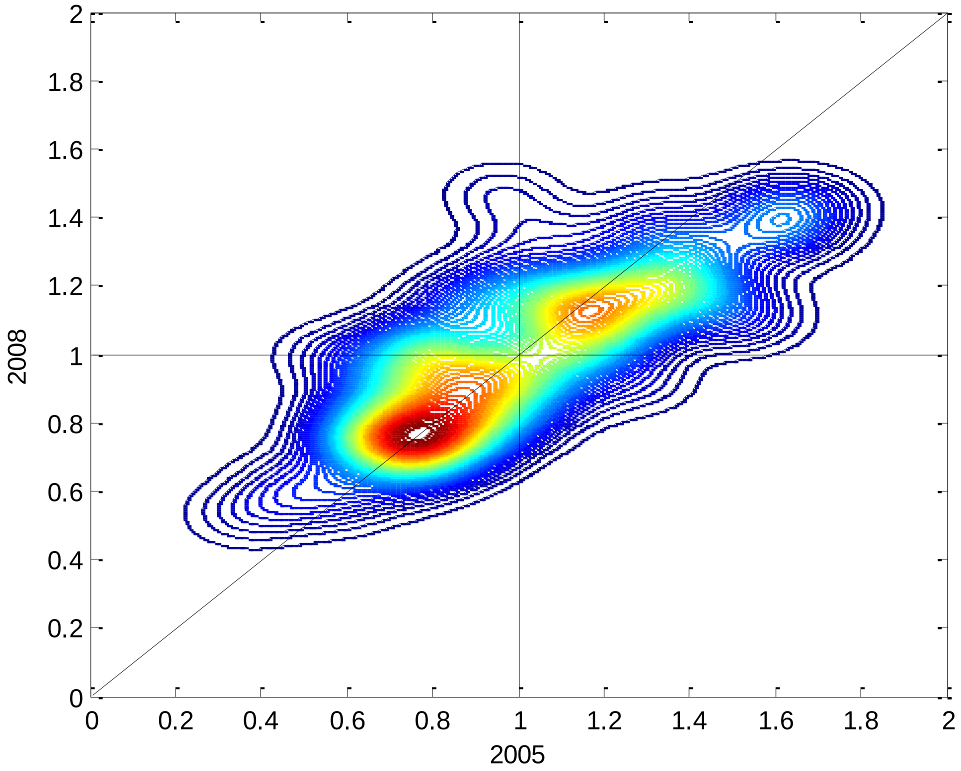



Figure 2.17 shows the corresponding contour of the conditional distribution. As can be seen, probability mass is concentrated on the 45-degree line. In other words, most local authorities tend to stay in the same positions and thus the initial difference is persistent over the period. This pattern in the distribution of recycling rates implies a lack of catch-up or convergence in recycling rates across local authorities. Just as in Figure 2.16, we can observe two peaks; one is well below the average and the other with lower concentration is just above the average.

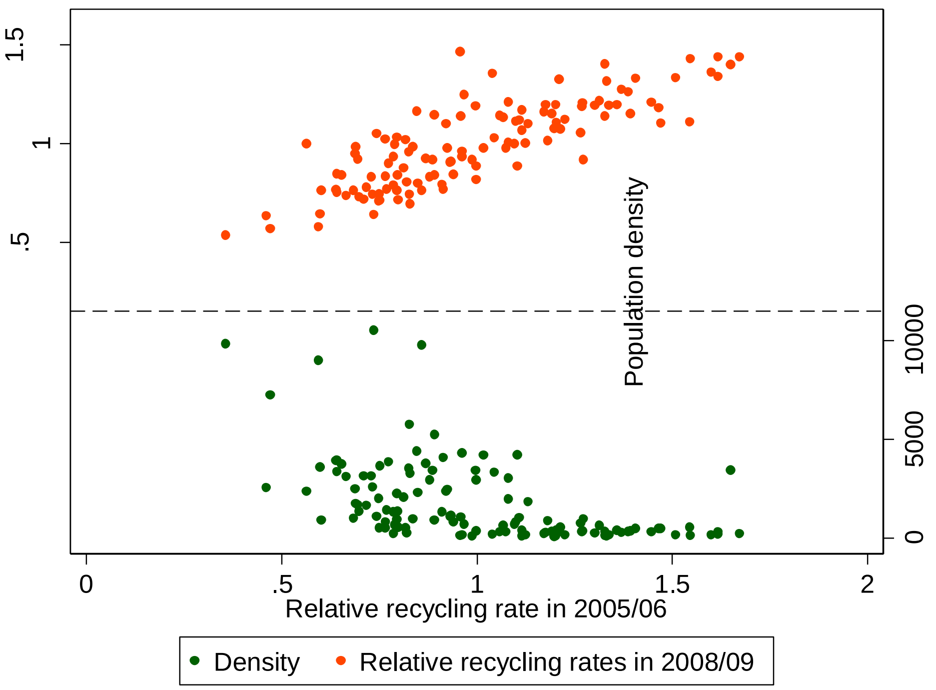
This provides suggests club convergence dynamics whereby local authorities performing at similar levels converge towards each other but diverge away from different clubs. It is particularly obvious in Figure 2.17 that one cluster occurs below the average level and the other occurs above the average. Considering policy settings in the second period, we may conclude that with more intensive incentive-based waste policies such as the LATS and the Landfill Tax Escalator, there appears to be a pattern of polarisation between high-performing local authorities and low-performing authorities while the middle group of local authorities in terms of recycling rates appears to vanish.

As Quah (1997) notes, such emerging twin-peaks patterns shed light on shortcomings of conventional approaches to convergence (i.e. cross-sectional or panel-data econometric methods) which provides only average estimates of cross-sectional convergence. Furthermore, as the data show explicit patterns of clustering together into two distinct clubs, the assumption of random sampling taken in the standard statistical inferences is violated. Therefore, to make proper inference, the conventional approach to convergence should explicitly address such emerging patterns of cross-section interaction. This leads on to the need for systematic analysis of cross-section data while examining geographic patterns of data and the evolution of spatial effects in the next section.

In an attempt to identify the distinctive features of local authorities in each club, Figure 2.8 plots population density on the distribution dynamics of the second period. As can be seen, local authorities in a clustering of recycling rates lower than the national average can be characterised by higher density than those in a clustering of higher rates. While the range of population density for the lower club is rather wide, it is obvious that high performing local authorities generally have a population density lower than 1000 per square km.

Appendix 2.10 splits local authorities between the highest and lowest 20 in terms of population density. Almost all of the highest 20 local authorities in population density are unitary authorities and move to a lower level of relative recycling below the national average or persistently remain in low rates of recycling, except Greenwich borough. In particular, 9 out of the highest 10 local authorities are all London boroughs. On the other hand, the lowest 20 local authorities are mostly waste disposal authorities and recycle above the national average in both years, except two unitary authorities, i.e. East Riding of Yorkshire and West Berkshire.

**Figure 2.18: Relative recycling rates and population density**




## 2.9 Spatial Data Analysis

### 2.9.1 Spatial Autocorrelation

To assess spatial dependence in recycling rates between neighbouring local authorities, the first step is to construct a spatial weight matrix whose elements specify the relative strength of interdependence between each pair of local authorities. There are many types of weight matrices. The simplest one is a binary contiguity-based weights matrix which considers shared borders to define a location's neighbours.

Using polygon-based geographical data, the distance information between 120 local authorities is obtained. The average distance between local authorities is 19.293 km. This may primarily depend on the area size of the observations. The maximum distance is 70.462 km. The minimum and maximum distances provide information on the shortest and longest distance to the nearest neighbour of all observations. Thus, the maximum distance value implies no neighbours within 70.462 km for that particular local authority.

Given this information, a weight matrix defines the structure of spatial spillovers or interactions between geographical units. 70.462 km is the minimum allowable distance cut-off for all local authorities to have neighbours. Since zero number of neighbours generally invalidates the statistical properties of spatial autocorrelation tests, the spatial weights matrix needs to be constructed based a distance cut-off value set at least greater than this minimum allowable value. Based on this consideration, 80 km is chosen as a threshold value and an inverse distance weights matrix is selected to allow for distance decay effects within the chosen threshold distance value. That is, the weights matrix takes zero for diagonal elements and an inverse distance for off-diagonal elements, formally given by:

$$\begin{cases} w_{ij}^{*} = 0 & \text{if } i = j \\ w_{ij}^{*} = \dfrac{1}{d_{ij}} & \text{if } d_{ij} \leq 80\,km \text{ and } w_{ij} = \dfrac{w_{ij}^{*}}{\sum_{j} w_{ij}^{*}} \\ w_{ij}^{*} = 0 & \text{if } d_{ij} > 80\,km \end{cases} \qquad \textbf{(2.24)}$$

where $w_{ij}$ is a row-standardised element in the spatial weights matrix of a pair $i$ and $j$. Table 2.9 summarises the information contained in a row-standardised inverse distance matrix with a cut-off distance of 80 km. Other values for cut-off distance, such as 100 km and 120 km, are also used to construct the inverse distance weight matrix. Furthermore, different types of weights matrices (e.g. the fixed distance weights matrix and *k*-nearest weights matrix) are also constructed using various distance cut-off values (e.g. 80 km, 100 km, and 120 km) and various values of *k* (e.g. the nearest 10, 15, 20, and 25 neighbours). The off-diagonal elements of these two weights matrices take 1 if a location, *j* is located within the critical cut-off value from a target location *i* (i.e. $w_{ij}$=1 if $d_{ij} \leq$ 80 km, 100 km or 120 km) or belong to the nearest *k* number of neighbours of a location, *i*, and otherwise 0.

**Table 2.9: The Summary of the spatial weights matrix**

| **Inverse distance with a cut off distance of 80 km** | |
|---|---|
| Number of Features | 120 |
| Percentage of Spatial Connectivity | 15.93 |
| Average Number of Neighbours | 19.12 |
| Minimum Number of Neighbours | 1 |
| Maximum Number of Neighbours | 35 |

Spatial autocorrelation measures the degree to which a variable of interest is correlated in space. To assess spatial autocorrelation, two widely used tests are employed: Moran's *I* and Getis-Ord General *G*. Moran's *I* provides information on whether geographical units are globally clustered or not. General *G* further identifies whether clustering occurs in high values or low values.

First of all, Moran's *I* as the best known measure of global spatial autocorrelation is defined as (Moran, 1950):

$$I = \frac{n}{S_0} \cdot \frac{\sum_i \sum_j w_{ij} \cdot (x_i - \mu) \cdot (x_j - \mu)}{\sum_i (x_i - \mu)^2} \qquad \textbf{(2.25)}$$

where *n* is the number of observations, $x_i$ and $x_j$ are observations for location $i$ and $j$, $w_{ij}$ is the element in the spatial weights matrix of a pair $i$ and $j$, and $S_0$ is a scaling constant, $S_0 = \sum_i \sum_j w_{ij}$. For a row-standardised spatial weights matrix $S_0 = n$.

For statistical inference, a standardised z-score for Moran's *I* is constructed:

$$z_I = \frac{I - E(I)}{\sigma(I)} \qquad \textbf{(2.26)}$$

where *E(I)* is the theoretical mean, computed as -1/($n$-1) and *σ(I)* is standard deviation. A statistically significant and positive *z*-score for Moran's *I* indicates spatial clustering among similar values, either high values or low values. On the other hand, a statistically significant and negative *z*-score for Moran's *I* indicates negative spatial autocorrelation or clustering of dissimilar values, such as regions with low values having neighbours with high values. Statistically insignificant or zero value of *z*-score indicates a random spatial pattern.

The Getis-Ord General *G* analysis is defined as (Getis and Ord, 1992):

$$G = \frac{\sum_i \sum_j w_{ij} \cdot x_i x_j}{\sum_i \sum_j x_i x_j} \qquad \textbf{(2.27)}$$

If the null hypothesis of no spatial clustering is rejected, then the sign of the *z*-score becomes important. A standardised *z*-score for General *G* is:

$$z_G = \frac{G - E(G)}{\sigma(G)} \qquad \textbf{(2.28)}$$

where *E(G)* is the theoretical mean, computed as $\sum_i \sum_j w_{ij} / n(n-1)$ and *σ(G)* is standard deviation. A statistically significant and positive *z*-score of General *G* indicates high values for the attribute cluster spatially. On the other hand, a statistically significant and negative *z*-

score indicates that low values cluster spatially.

Moran's *I* and General *G* are conducted based on the inverse weights matrix with a cut-off distance of 80 km. Table 2.10 provides the test results of spatial autocorrelation in relative recycling rates across local authorities each year. As can be seen, Moran's *I* statistics are all highly significant for every year. This suggests the null of no spatial autocorrelation is rejected and the distribution of recycling rates is spatially clustered throughout the study period. However, it is noticeable that the strength of spatial effects decreases over the period as *z*-scores of Moran's *I* decrease except for one year, between 2005 and 2006. Larger and more statistically significant spatial dependence in the earlier years can be related to high tendency of mobility in the first period but persistence in the second period.

**Table 2.10: Spatial statistics for relative recycling rates using the inverse 80 km weights**

| Year | Moran | | | Getis Ord | | |
|---|---|---|---|---|---|---|
| | I | *z*-score | p-value | G | *z*-score | p-value |
| **1998** | 0.464659 | 12.046440 | 0.000000 | 0.009407 | 5.812213 | 0.000000 |
| **1999** | 0.406140 | 10.439190 | 0.000000 | 0.009151 | 4.419380 | 0.000010 |
| **2000** | 0.409100 | 10.490011 | 0.000000 | 0.009070 | 4.272533 | 0.000019 |
| **2001** | 0.348517 | 8.955092 | 0.000000 | 0.008725 | 2.405586 | 0.016147 |
| **2002** | 0.361821 | 9.291655 | 0.000000 | 0.008546 | 1.235397 | 0.216683 |
| **2003** | 0.261526 | 6.763975 | 0.000000 | 0.008271 | -1.456981 | 0.145122 |
| **2005** | 0.178904 | 4.698903 | 0.000003 | 0.008188 | -2.943323 | 0.003247 |
| **2006** | 0.240917 | 6.256307 | 0.000003 | 0.008264 | -2.247981 | 0.024577 |
| **2007** | 0.211538 | 5.519010 | 0.000003 | 0.008259 | -2.553059 | 0.010678 |
| **2008** | 0.181250 | 4.753111 | 0.000002 | 0.008252 | -2.815110 | 0.004876 |

*Notes:* The theoretical expected value is constant for all years. $E(I)$=-0.008403.

General *G* statistics show mixed results in terms of both statistical significance and signs on z-score. While recycling rates in 2002 and in 2003 does not have any pattern of spatial clustering, the rest were clearly divided into two patterns. Statistically significant and positive *z*-scroes of General *G* between 1998 and 2002 imply that clustering dominantly occurred in high values whereas statistically significant and negative *z*-scores between 2005 and 2008 mean clustering of low values. This is consistent with the pattern shown in the stochastic kernel of the second period where a higher peak emerges below the national average.

The results of the same statistics based on other types of weights matrices with varying distance cut-off values are reported in Appendix 2.11. While the Moran's *I* statistics are all significant regardless of spatial weights matrices, the results of General *G* are mixed across matrices. Particularly, the fixed weights matrices tend to produce statistically insignificant results for the second period while the inverse distance matrices and the *k*-nearest weights matrices produce similar results.

### 2.9.2 Beta Convergence with Spatial Effects

Given the results of the preceding section, the analysis of convergence needs to take into account spatial dependence in the distribution of recycling rates. In regression analysis, spatial autocorrelation is taken into account in two distinct ways: the substantive form and nuisance form of spatial effects. Different combinations of these two approaches produce various spatial process models. The first approach is referred to as the spatial lag model (or substantive spatial dependence) and the second is referred to as the spatial error model. The regression in the context of convergence of recycling rates is as follows:

$$g_i = \alpha + \beta \ln(\text{Recycling}_{i0}) + \rho W g_i + \gamma Z_i + \varepsilon_i \qquad \textbf{(2.29)}$$

where $g_i = \frac{1}{T}\ln(\text{Recycling}_{it} - \text{Recycling}_{i0})$, i.e. the average growth of recycling rates for local authority $i$ over $T$ years. $\rho$ denotes the spatial autoregressive parameter and $\varepsilon$ is the error term with the usual properties. Due to the endogeneity of the spatially lagged dependent variable, $\rho W g_i$, the OLS estimates will be biased and inconsistent for the spatial lag model. Therefore the maximum multiplier (ML) technique and IV estimation are commonly used to obtain consistent estimates of the lag model. The reduced form of the spatial lag model is:

$$g_i = (I - \rho W)^{-1}[\alpha + \beta \ln(\text{Recycling}_{i0}) + \varepsilon_i] \qquad \textbf{(2.30)}$$

where $(I- \rho W)^{-1}$ is called a spatial multiplier. Then the marginal effect of an increase in the initial income on the growth rate is (Abreu at el., 2005, p.31):

$$\partial g_i / \partial \ln(\text{Recycling}_{i0}) = (I - \rho W)^{-1} \beta = I\beta + \rho W \beta + \rho^2 W^2 \beta + \rho^3 W^3 \beta + \rho^4 W^4 \beta \cdots \qquad \textbf{(2.31)}$$

The interpretation is as follows. The first term is the "direct effects" which the initial recycling rate of local authority $i$ has on its own growth rate, and the second term is interpreted as "indirect effects" which the initial recycling rates of neighbouring authorities, for example $j$ identified by $W$, have on the growth rate of authority $i$. The remaining terms represent "induced effects" which include the impacts of higher-order neighbours (Abreu at el., 2005, p.32). Induced effects have particularly important implications on the global nature of spatial links developed in the spatial lag model. That is, recycling performance of one particular local authority influences the whole system in the spatial lag model.

The second approach is the spatial error model. This is formally:

$$g_i = \alpha + \beta \ln(\text{Recycling}_{i0}) + \gamma Z_i + \varepsilon_i \qquad \textbf{(2.32)}$$

where $\varepsilon_i = \lambda W \varepsilon_i + \mu_i$ and hence $\varepsilon_i = (I - \lambda W)^{-1} \cdot \mu_i$. $\lambda$ is the spatial autoregressive parameter, similar to $\rho$ in the spatial lag model. As in the spatial lag model, a spatial multiplier, $(I-\lambda W)^{-1}$, can be expressed as an infinite series and this will ensure a shock at location $i$ to be transferred across neighbours. The spatial error model can be transformed to the spatial Durbin representation or spatial common factor model by substituting $\varepsilon = (I-\lambda W)^{-1} \mu$.

$$g_i = \alpha + \beta \ln(\text{Recycling}_{i0}) + \lambda W g_i - \lambda \cdot \beta \cdot W \ln(\text{Recycling}_{i0}) + \gamma Z_i + \mu_i \qquad \textbf{(2.33)}$$

Without the parametric constraint on the spatial lag of the initial recycling rate, the model can be expressed as:

$$g_i = \alpha + \beta \ln(\text{Recycling}_{i0}) + \lambda W g_i - \zeta \cdot W \ln(\text{Recycling}_{i0}) + \gamma Z_i + \mu_i \qquad \textbf{(2.34)}$$

Given these two forms of spatial effects, a general version of the spatial model includes both the spatial lag term and a spatially correlated error structure:

$$g_i = \alpha + \beta \ln(\text{Recycling}_{i0}) + \rho W_1 g_i + \gamma Z_i + \varepsilon_i \qquad \textbf{(2.35)}$$

where $\varepsilon_i = \lambda W_2 \varepsilon_i + \mu_i$ and hence $\varepsilon_i = (I - \lambda W)^{-1} \cdot \mu_i$. We might simply assume that the spatial weights matrices, $W_1$ and $W_2$ are equal while the identification of each weight matrix may involve the comparison of regression results with various weights in terms of statistical significance.

In the following, the spatial econometric models for convergence of recycling rates are specified using the above four forms; the spatial lag model, spatial error model, spatial Dubin model without the parametric constraint and the general model. They are estimated using either ML or GMM. The weight matrix, $W$, is the row-standardised inverse weights matrix with a cut-off distance of 80 km. However, the regression results do not significantly vary with other types of weights or other values of cut-off distance. For the general model, the two weights on the spatial lag and error terms are assumed equal. The results for the convergence regressions without explanatory variables, $Z$, are reported in Table 2.11 and Table 2.12 for the first and the second period respectively.

The presence of convergence is supported in all the above spatial regressions although spatial effects are mostly insignificant except the residual spatial autocorrelation in the general model. The OLS estimates of the model without spatial effects are again reported to readily compare with the results of spatial models. Before running spatial models, the presence of spatial dependence in error terms is examined using tests like Moran's $I$ for regression residuals and the Lagrange multiplier test, i.e. LMERROR.

As can be seen in Table 2.11, the null of no spatial autocorrelation in OLS residuals is not rejected in both tests. This is confirmed by the results of the spatial error model where $\lambda$ is statistically insignificant. With respect to the spatial lag model, the spatial autoregressive coefficient, $\rho$, is also statistically insignificant. These results are all consistent with the GMM estimates. However, in the general model, spatially correlated error terms are found statistically significant. In other words, the specification of spatial effects should include both a substantive form and a residual form. However, the spatial lag term is not statistically significant which implies that there are no direct spillovers from neighbours whilst spatially clustered error terms are statistically significant. This nuisance form of spatial effects may capture spatial dependence in unmeasured explanatory variables. This can also be interpreted as indicating that a local authority's growth in recycling activities is affected by growth in neighbouring authorities only to the extent that neighbours have above or below the normal growth. Such results are consistently obtained with the use of other weights matrices, such as the inverse weights matrix with a cut-off distance of 100 km, the fixed weights matrix with a cut-off distance of 80 km and 100 km and the 10 nearest weights matrix.

The size of $\beta$ slightly increases compared to the aspatial model, which implies a faster speed of convergence. This may suggest that spatial effects accelerate the movement on the transitional path towards the steady-state. The results for the second period are the same while the extent of an increase in $\beta$ with the inclusion of spatial effects is a bit greater than the first period.

**Table 2.11: Estimation results of spatial beta convergence model 1998/99-2003/04**

| variable | Aspatial model | Spatial model | | | | | |
|---|---|---|---|---|---|---|---|
| | | ML | | | GMM | | |
| | | Error | Lag | Durbin | Error | Lag | General |
| **constant** | 0.377733*** | 0.379367*** | 0.370244*** | 0.328603*** | 0.382872*** | 0.371905*** | 0.277994*** |
| | (21.259343) | (20.236338) | (10.496676) | (4.399864) | (18.507741) | (9.838678) | (9.982338) |
| **ln(Recycling1998)** | -0.113359*** | -0.113744*** | -0.111870*** | -0.115339*** | -0.114594*** | -0.112199*** | -0.115670*** |
| | (-13.369835) | (-12.841881) | (-10.752566) | (-10.217127) | (-11.992516) | (-10.396784) | (-10.803542) |
| **λ** | | 0.121000 | | | 0.296689 | | 0.288302*** |
| | | (0.643443) | | | (0.376202) | | (4.545092) |
| **ρ** | | | 0.029957 | 0.122968 | | 0.023329 | -0.037702 |
| | | | (0.256730) | (0.654725) | | (0.174872) | (-0.239578) |
| ***W*•ln(Recycling1998)** | | | | 0.017655 | | | |
| | | | | (0.659588) | | | |
| $R^2$ | 0.6024 | 0.6044 | 0.6020 | 0.6022 | 0.6045 | 0.6026 | 0.6063 |
| **Adjusted** $R^2$ | 0.5990 | 0.6011 | 0.5987 | 0.5954 | 0.6011 | 0.5993 | 0.6030 |
| **Log-likelihood** | | 217.1764 | 217.0027 | 217.2029 | | | |
| **MORAN** | 0.02907 | | | | | | |
| **LMERROR** | 0.4887 | | | | | | |
| **LMSAR** | | | 0.6736 | | | | |

*Notes*: t-values are in parentheses. Significance is indicated by *, **, *** for 0.1, 0.05 and 0.001 level, respectively. MORAN is the Moran's I test adapted to OLS residuals (Cliff and Ord, 1981). LMERROR is the Lagrange multiplier test for spatial autocorrelation in the OLS residuals and LMSAR is the Lagrange multiplier test for spatial autocorrelation in the residuals of the spatial lag model (Anselin, 1988).

**Table 2.12: Estimation results of spatial beta convergence model 2005/06-2008/09**

| | | Spatial | | | | | |
|---|---|---|---|---|---|---|---|
| | **Aspatial** | **ML** | | | **GMM** | | |
| **Variable** | | Error | Lag | Durbin | Error | Lag | General |
| **constant** | 0.521435*** | 0.527293*** | 0.532900*** | 0.376168*** | 0.539799*** | 0.599456*** | 0.322235*** |
| | (12.474995) | (12.468377) | (10.295824) | (3.070741) | (12.151265) | (8.548693) | (8.908707) |
| **ln(Recycling2005)** | -0.124322*** | -0.126147*** | -0.125256*** | -0.132002*** | -0.129982*** | -0.130678*** | -0.130405*** |
| | (-9.516949) | (-9.572551) | (-9.390017) | (-9.540624) | (-9.508486) | (-9.313927) | (-9.613038) |
| **λ** | | 0.122000 | | | 0.398770 | | 0.452422*** |
| | | (0.649150) | | | (0.517368) | | (24.797019) |
| **ρ** | | | -0.061997 | 0.078998 | | -0.441910 | -0.364607 |
| | | | (-0.409420) | (0.412617) | | (-1.398299) | (-0.948342) |
| ***W*•ln(Recycling1998)** | | | | 0.050755 | | | |
| | | | | (1.417645) | | | |
| **$R^2$** | 0.4342 | 0.4373 | 0.4375 | 0.4440 | 0.4355 | 0.4208 | 0.4635 |
| **Adjusted $R^2$** | 0.4295 | 0.4325 | 0.4327 | 0.4345 | 0.4307 | 0.4159 | 0.4589 |
| **Log-likelihood** | | 251.5416 | 251.3969 | 252.4565 | | | |
| **MORAN** | 0.0297 | | | | | | |
| **LMERROR** | 0.5096 | | | | | | |
| **LMSAR** | | | 0.9804 | | | | |

*Notes*: See notes for Table 2.11.

### 2.9.3 Sigma Convergence with Spatial Effects

Conventionally, a downwards trend in the sample variance, $s^2$, is viewed as evidence of declining cross-sectional dispersion. However, the formula for sample variance is only valid under the assumption of homogeneity and no autocorrelation. In order to show the possibility of autocorrelation and even heterogeneity, the variance can be decomposed as follows (Rey and Dev, 2006, p.227):

$$s^2 = \sigma^2\theta \quad \text{where } \theta = \frac{1}{n-1}\left[\sum_{i=1}^{n}(\mu_i^2 + \omega_{i,i}) - \frac{1}{n}\sum\sum_{i=1}^{n}(\mu_i\mu_j + \omega_{i,j})\right] \qquad \textbf{(2.36)}$$

$\sigma^2$ is aspatial component. When $\mu_i \neq \mu_j \neq \ldots\ldots.. \neq \mu_n$, mean heterogeneity presents. When $\omega_{1,1}^2 \neq \omega_{2,2}^2 \neq \ldots\ldots.. \neq \omega_{n,n}^2$, we have variance heterogeneity (i.e. heteroscedasticity). Spatial dependence is reflected from non-zero off-diagonal elements, $\omega_{i,j}$.

In the conventional use of sample variance, the parameter, $\theta$, is set equal to 1. We have already seen in the previous section that the sample variance of recycling rates in level terms increases over time under this assumption which implies the lack of sigma convergence in a conventional sense. However, when the data is spatially correlated, there is risk of confusing changes in sample variance with changes in the extent of spatial autocorrelation. In other words, $\theta$ is unlikely to equal 1 and hence the sample variance is no longer the appropriate global dispersion parameter. Furthermore, the extent of spatial autocorrelation may also change over time. Therefore, the presence of spatial dependence as well as this dynamic nature of spatial dependence should also be included when constructing the measure of global dispersion.

Rey and Dev (2006) propose specifying a spatially dependent dispersion parameter using spatial process models. That is, the cross-sectional variance obtained from spatial process models can be used as the global dispersion parameter. Relative recycling rates at time $t$, $RR_t$, defined earlier, are used to control for the assumption of mean homogeneity.

Using the spatial lag model, the following regression is estimated for each year.

$$RR_t = c + \rho W \cdot RR_t + \gamma Z_t + \varepsilon_t \qquad \textbf{(2.37)}$$

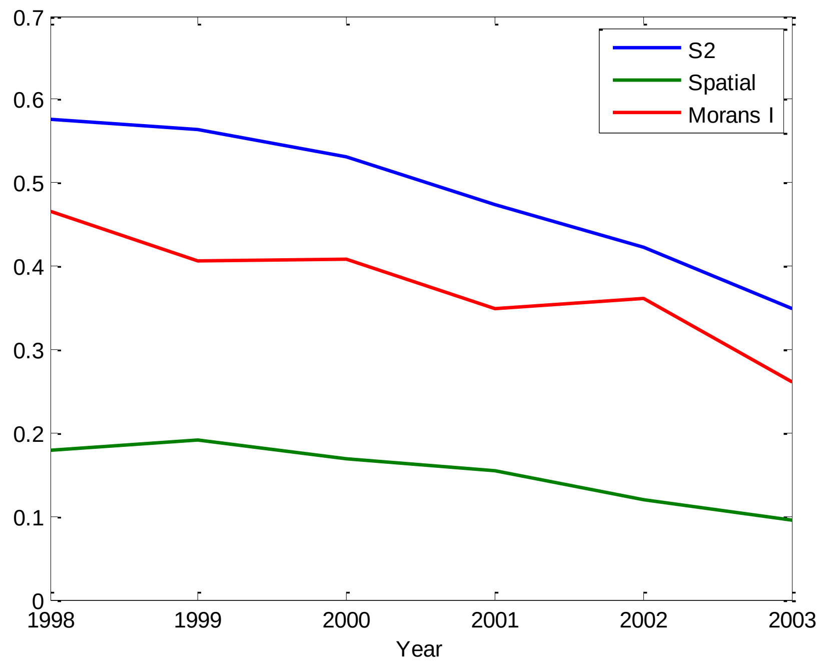
The dependent variable, $RR$, has the following normal distribution:

$$RR \sim N((I - \rho W)^{-1}\gamma Z,\ \sigma^2 (I - \rho W)^{-1}(I - \rho W')^{-1}) \qquad \textbf{(2.38)}$$

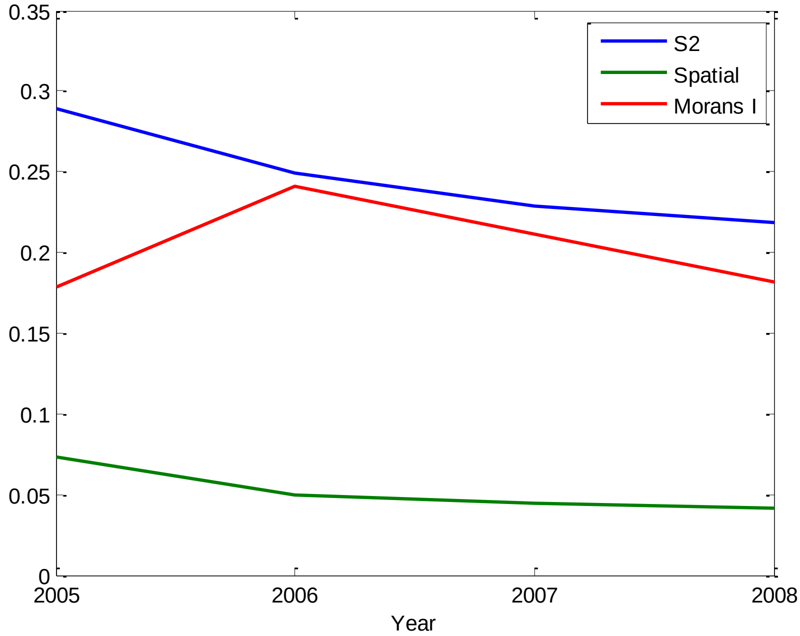
The spatial lag and error model produce the same variance according to the theory (Rey and Dev, 2006, p.221). $\rho$ is the spatial parameter and the row-standardised inverse weight matrix with a cut-off distance of 80 km is employed for $W$.

**Figure 2.19: Sigma convergence in the presence of spatial effects**

(a) 1998/99-2003/04



(b) 2005/06-2008/09




Figures 2.19 (a) and (b) visualise the conventional dispersion parameter and the ML estimates of the global variance parameter from spatial lag model for the first and second period respectively. Changes in spatial autocorrelation are also shown by Moran's *I* statistics of relative recycling rates over time in both periods.

As can be seen, first, the presence of sigma convergence is in general supported for both periods. Second, comparing the conventional parameter and the global dispersion parameter from the spatial process model, a downward trend is clearer in the former whilst the latter shows only a moderate decrease over time in both periods. Third, the former always indicates larger dispersion than the latter measure. Fourth, from Moran's *I* statistics, the magnitude of spatial clustering in general decreases over the first period. However, in the second period, spatial dependence increases in the first year (2005/06-2006/07). Although there is a decrease in the following years, the initial level of spatial dependence is reached again in the final year. The pattern and extent of changes in spatial effects in the second period may be interpreted in the context of the introduction of LATS in 2005. The scheme may initially increase spatial interaction as observed. However, geographical closeness may matter less in trading permits in the long term. This may be shown by a decrease in spatial autocorrelation in the following years.

Finally, comparing the two periods, the extent of changes in both the sample variance and the global dispersion parameter is smaller in the second period which suggests a rather weak pattern of convergence. This conforms to the analysis of distribution dynamics in the preceding section in which the second period is characterised by persistence whilst there is active catch-up in low recycling rates in the first period.

## 2.10 Conclusion

Environmental convergence has been investigated in numerous studies of air pollutants, but not in terms of waste pollutants. The current study hypothesises strategic interaction among local authorities based on yardstick competition to achieve national and local targets for recycling rates. The interdependence that arises from informational externalities may lead to convergence of recycling rates across local authorities. Therefore, the study investigates the presence of convergence using various concepts of convergence. This approach provides a comprehensive analysis of the distribution of recycling rates.

The study utilises data on recycling rates across local authorities in England. It is of special interest to investigate how recycling performance at a decentralised level has evolved over the last decade during which we have observed considerable changes in the UK waste policy. Notably, the Landfill Tax Escalator and the LATS started taking effect from 2005. The dynamic efficiency effects of such market-based instruments are anticipated to enhance intergovernmental interaction and thus to increase the speed of convergence. Thus, the study period is divided into two (i.e. the first period, 1998-2003 and the second period, 2005-2008) to distinguish the move to the implementation of more intensified market-based instruments at a local authority level.

The convergence analysis takes three commonly used approaches in previous literature on emissions convergence: dispersion parameters for sigma convergence, a regression approach for beta convergence and nonparametric methods for distribution dynamics. There is strong evidence of the presence of convergence in a global sense. In the examination of sigma convergence, various dispersion measures of logged recycling rates over time clearly show a downward trend in the spread of recycling rates in distributions.

From the cross-sectional regression analysis of beta convergence, both periods show a statistically significant and negative relationship between the initial recycling rates and the growth rate, which implies the presence of convergence across local authorities in a conditional sense as we detect statistically significant influence of some socio-demographic factors. Of these factors, it is noticeable that densely populated cities tend to have a lower recycling growth rates. In other words, population density determines each authority's steady-state level of recycling as well as the speed with which they approach their own steady state. The speed of convergence is faster in the first period with a half-life between 3.27 and 4.13 years than in the second period with a half-life between 5.15 and 7.42 years.

More specific and interesting characteristics of convergence process are detected using nonparametric methods for each period. While the average recycling rates increased over the whole period, the period before 2005 showed that recycling performance across the entire distribution improved relative to the average recycling rate. Particularly, the presence of convergence in the first period occurs largely because of an improvement in the recycling rates of poor-performing local authorities. On the other hand, the second period shows persistent disparities in the overall distribution and there emerge two significant groupings of local authorities with either higher or lower rates than the national average. Although lower rates are more frequently encountered, the division into two clubs implies polarisation between low-performing and high-performing local authorities.

In the latter part of the analysis, a global spatial analysis is conducted to examine the presence of spatial dependence in the distribution of recycling rates. There is strong evidence of geographical clustering of similar recycling rates in relative terms while the magnitude of spatial effects generally decreases over the period. The nature of the weakening of clustering in times of convergence can be interpreted in two ways: local authorities in each cluster become dissimilar or the number of clusters reduces.

The General *G* statistics show that in general, the first period is characterised by clustering of high values whilst a clustering in low values is statistically significant in the second period. This confirms the results of stochastic kernel which show that a larger portion of the probability clusters below the national average in the second period.

The implications of spatial effects in the process of convergence are also investigated by estimating spatial process models for sigma convergence as well as beta convergence. The proximity between local authorities may play a significant role in the extent of informational externalities because an exchange of their knowledge or know-how is easier between geographically close neighbours. Therefore, it is necessary to take into account spatial dimension of externalities in the process of convergence.

In beta convergence, such spatial effects may be captured by the substantive form i.e. the spatial lag of recycling rates. The results show that the model with both substantive form and nuisance form of spatial effects are statistically the most significant specification as a spatial beta convergence model. However, spatial effects are statistically significant only through error terms. The presence of convergence with strong nuisance spatial dependence in recycling performance across local authorities implies that the process of convergence can be partly explained by spatially correlated omitted variables rather than direct diffusion in terms of waste management practices or environmentally efficient technology across local authorities. Another interpretation of nuisance spatial dependence is that spatial interaction across local authorities is significant only to the extent that growth of neighbouring authorities deviates from the normal rate. The sigma convergence in the presence of spatial dependence is confirmed by a declining trend of global dispersion parameters over time.

The observed overall pattern as well as distinct patterns of convergence and spatial dependence between the first and second period can be explained as follows. Firstly, returning to the hypothesis posed for the source of convergence, the evidence of catch-up and global pattern of convergence in both periods support the spillover framework to explain progress in recycling performance across local authorities. The spatial exploratory analysis on recycling rates also suggests that informational spillovers across local authorities involve spatil patterns in nature.

However, the distribution pattern of two convergence clubs suggests a stronger interaction between local authorities at the similar level of recycling activities but overall divergence between dissimilar groups of local authorities. The limited convergence between some, rather than all could be an efficient way to improve performance in the short term as difficulties experienced by local authorities in dealing with waste may vary depending on the level of performance and thus interaction between similar performers will be a more effective way to approach the problems of managing waste. This implies that different types of authorities choose more carefully with whom they benchmark. For example, most poor-perfoming local authorities are highly dense urban areas. One of challanging issues shared among urban areas is to design effective collection services to overcome a lack of space for storage and difficulties transporting materials to collection point for flats and estates. Thus strategic cooperation among those areas with same concerns and interests will be more effective and cost efficient in developing a benchmark scheme than global interactions.

Whilst the new waste policies lead to locally convergent recycling performance, it is expected to provide greater incentives to exploit spillover benefits from local authorities advanced in recycling. In the long run, this will reduce the gap between dissimilar groups of local authorities and lead to global convergence. Considering a short span of time studied for the second period, the observed performance may represent only a short-term feature of convergence. This may provide a reason why the process of global convergence is shown slow in the second period. Therefore, a further study should include a longer time period to capture the full effects of the new set of waste policies.

However, it is also notable that landfill permits have not been actively traded under the LATS. Local authorities easily meet their landfill reduction targets without trading, and the quantity of waste diverted from landfills always far exceeds the target given the permit allocation. This may imply that spatial externalities generated by the LATS are less significant than expected. Although spatial dependence is statistically significant probably due to the Landfill Tax Escalator and other funding schemes which still provide a stronger incentive to interact across local authorities, the scale of interaction does not increase but decrease over the period. Although the Government announced the ending of the LATS from 2012/13, in order to improve the effectiveness of the scheme, the total allowed landfill disposal should be capped at a lower level.

Finally, the observed inter- and intra-distribution of recycling rates help us to analyse different scenarios for future distribution and to draw some policy implications. If the overall improvements in recycling rates continue, further polarisation might not be a big problem. If not, further polarisation with the currently observed bigger cluster of low rates may hamper any national targets for recycling rates. Therefore, the Government should take some complementary measures to reduce polarisation between high and low rates in future. Considering density is a crucial factor which determines the long-run level of recycling but in a negative way, new measures should target densely populated urban areas such as an initiative providing funding to establish recycling facilities close to the city.

One of caveats of this study is that recycling performance is measured in terms of weight, not volume. Furthermore, recycling rates are measured at the aggregate level, including all recycled materials. Thus, if glass takes a large portion of total recycled waste, a high recycling rate is inevitable. In future, with the availability of data, it will be more accurate and interesting to look at a particular material recycled separately or use volume data in order to avoid this type of bias towards high recycling rates with large glass recyclables. Moreover, this could allow us to identify long-term determinants of recycling rates for each material which may further provide us more specific ideas on households' as well as local authorities' decisions on waste disposal method.

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## Appendix 2.1: Landfill Tax rates

| Date of change | Standard rate (£ per tonne) | Lower rate (£ per tonne) |
|---|---|---|
| 01.10.1996 | 7 | 2 |
| 01.04.1999 | 10 | 2 |
| 01.04.2000 | 11 | 2 |
| 01.04.2001 | 12 | 2 |
| 01.04.2002 | 13 | 2 |
| 01.04.2003 | 14 | 2 |
| 01.04.2004 | 15 | 2 |
| 01.04.2005 | 18 | 2 |
| 01.04.2006 | 21 | 2 |
| 01.04.2007 | 24 | 2 |
| 01.04.2008 | 32 | 2.50 |
| 01.04.2009 | 40 | 2.50 |
| 01.04.2010 | 48 | 2.50 |
| 01.04.2011 | 56 | 2.50 |
| 01.04.2012 | 64 | 2.50 |
| 01.04.2013 | 72 | 2.50 |
| 01.04.2014 | 80 | 2.50 |

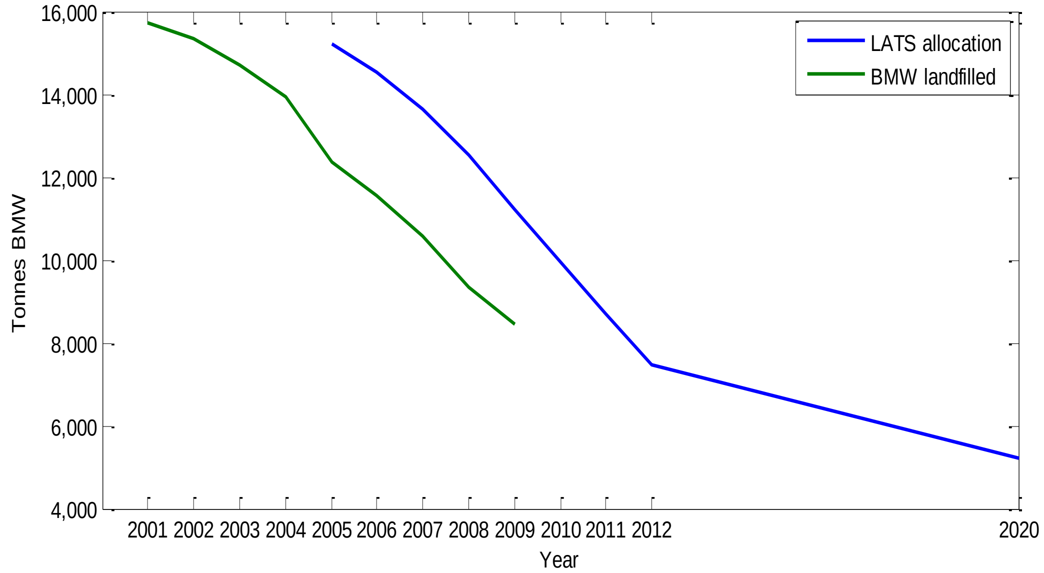
Source: HMRC Notice LFT1 (April 2011) A general guide to Landfill Tax.

## Appendix 2.2: Landfill Tax Credit Scheme (LTCS)

| Category | Description (Projects should conform to one of six objects set) |
|---|---|
| **Category A** | Projects that involve reclaiming land, the use of which has been prevented by some previous activity |
| **Category B** | Projects that reduce or prevent pollution on land |
| **Category D** | Projects that provide or maintain public amenities or parks within 10 miles of a landfill site |
| **Category DA** | Delivery of biodiversity conservation for UK species habitats |
| **Category E** | Projects to restore or repair buildings for religious worship, or of architectural or historical interest within 10 miles of a landfill site. |
| **Category F** | Fund the cost of administrative, financial or other similar services, supplied to other enrolled environmental bodies (EBs). |

## Appendix 2.3: LATS Allowance and Trading

### Table A2.3: LATS allowance and actual BMW sent to landfill




Source: Environment Agency, LATS Annual Report 2009/10

### Figure A2.3: Trading of LATS allowances

| Number of Trades | Period when trade took place | Average price (£) per allowance |
|---|---|---|
| 2 | 2007/08 | £29.50 |
| 3 | 2008/09 | £18.50 |
| 37 | 2009/10 | £4.84 |

Source: Environment Agency, LATS Annual Report 2009/10.

*Note*: 20 out of 37 trades in the 2009/2010 LATS year occurred during the reconciliation period in September 2010.

## Appendix 2.4: Summary of Key System Configurations in England, 2007

| | Recycling Container and Refuse Frequency | Total Number | % of English Authorities |
|---|---|---|---|
| **Kerbside Sort** | Sack and/or box, fortnightly refuse | 59 | 17 |
| | Sack and/or box, weekly refuse | 95 | 27 |
| | Total Kerbside Sort | 154 | 44 |
| **Single Stream Co-mingled** | Wheeled Bin, fortnightly refuse | 59 | 17 |
| | Wheeled Bin, weekly refuse | 24 | 7 |
| | Sack and/or box, fortnightly refuse | 7 | 2 |
| | Sack and/or box, weekly refuse | 31 | 9 |
| | Total Single Stream Co-mingled | 121 | 35 |
| **Two Stream Co-mingled** | Sack and/or box, fortnightly refuse | 17 | 5 |
| | Sack and/or box, weekly refuse | 20 | 6 |
| | Total Two Stream Co-mingled. | 37 | 11 |

Source: WRAP (2008. p.8)

*Note*: Two stream co-mingled systems are where materials are separated into two categories, usually fibres (paper/card) and containers (glass, cans and plastic bottles). Then separated materials are loaded into separate compartments on a twin compartment collection vehicle. There are a very few authorities where WRAP holds no collection information. The total percent of local authorities exclude those systems which cannot be classified into a common system type.

## Appendix 2.5: Educational Qualifications and their NVQ Equivalents

| | |
|---|---|
| **NVQ Level 5** | Higher degree |
| **NVQ Level 4** | First degree |
| | Other degree |
| | Diploma in Higher Education |
| | HNC, HND, BTEC etc higher |
| | Teaching - further education |
| | Teaching - secondary education |
| | Teaching - primary education |
| | Teaching - foundation stage |
| | Teaching - level not stated |
| | Nursing etc |
| | RSA higher diploma |
| | Other HE below degree |

## Appendix 2.6: Green Solow Model (Brock and Taylor, 2010)

Consider the standard theory of Solow model. With the Cobb-Douglas production function, the level of output, $Y$, is given by:

$$Y = F(K, BL) = K^{\alpha}(BL)^{1-\alpha} \qquad 0 < \alpha < 1 \qquad (1)$$

where $K$ is capital, $L$ is labour, and $B$ is labour augmenting total factor productivity (i.e. $BL$ is skilled labour). In order to trace the dynamics of each factor, assume that the level of capital is determined by an exogenously given saving rate, $s$ and a depreciation rate, $\delta$. Raw labour ($L$) grows at a rate equal to the population growth rate, $n$, and technology ($B$) evolves with an exogenously determined growth rate equal to $g_B$. Emission growth rate is given at $g_B$.

$$\dot{K} = sY - \delta K \qquad (2)$$
$$\dot{L} = nL, \quad \dot{B} = g_B B \qquad (3)$$
$$\dot{E} = g_E E \qquad (4)$$

To take into account the impact of pollution, assume every unit of economic activity, $F$, generates $\Omega$ units of pollution as a joint product of output. The amount of pollution abated is a constant return to scale activity, and is strictly concave function of the total economic activity and abatement efforts, $F^A$. At an abatement level, $A$, the unit of pollution removed from the total is $\Omega A$ and thus pollution emitted, $E$ is given by:

$$\begin{aligned} E &= \Omega F - \Omega A(F, F^A) \\ &= \Omega F[1 - A(1, F^A / F)] \qquad (5) \\ &= \Omega F \cdot a(\theta) \quad \text{where } a(\theta) = [1 - A(1, F^A / F)] \text{ and } \theta = F^A / F \end{aligned}$$

$\theta$ is the fraction of economic activity dedicated to abatement or abatement intensity. Combining the assumptions on emissions abatement with the Solow model, output available for consumption or investment becomes $Y = [1-\theta] F$. In per effective worker, the measure of output can be written as:

$$y = (1-\theta)F(K/BL, 1) = (1-\theta)f(k) = (1-\theta)k^{\alpha} \quad \text{where } k = K/BL \qquad (6)$$

Capital per effective worker evolves over time by:

$$\frac{\dot{K}}{BL} = \dot{k} = sk^{\alpha} - \delta k \qquad (7)$$

This further gives:

$$\left(\frac{\overset{\bullet}{K}}{BL}\right) = \dot{\tilde{k}} = s(1-\theta)k^{\alpha} - (g_B + n + \delta)k \qquad (8)$$

And the rate of change of capital per effective worker is:

$$\frac{\dot{\tilde{k}}}{k} = s(1-\theta)k^{\alpha-1} - (g_B + n + \delta) \qquad (9)$$

With the Inada conditions for $F$ and a fixed $\theta$, the economy converges to the equilibrium and on balanced growth path, we have $g_y = g_k = g_c = g_B > 0$. At the steady state, capital per effective worker and the corresponding income per effective worker is given by:

$$k^* = \left[\frac{s(1-\theta)}{g_B + n + \delta}\right]^{\frac{1}{1-\alpha}} \qquad (10)$$

$$y^* = (k^*)^{\alpha} = \left[\frac{s(1-\theta)}{g_B + n + \delta}\right]^{\frac{\alpha}{1-\alpha}} \qquad (11)$$

The derivation of emissions growth is:

$$E = \Omega F \cdot a(\theta) \quad \text{where } F(K, BL) = BL \cdot k^{\alpha} \qquad (12)$$

Taking logs and differentiating with respect to time gives:

$$\frac{\dot{E}}{E}=\frac{\dot{\Omega}}{\Omega}+\frac{\dot{B}}{B}+\frac{\dot{L}}{L}+\alpha\frac{\dot{\tilde{k}}}{k} \qquad (13)$$

$$g_E=-g_A+g_B+n+\alpha\frac{\dot{\tilde{k}}}{k} \qquad (14)$$

where $g_A$ is the rate of exogenous technological progress in abatement lowering $\Omega$ and $g_A>0$.

In steady state $\dot{\tilde{k}}=0$ and thus $g_E=-g_A+g_B+n$ (15)

Therefore, for sustainable growth, $g_B>0$ and $g_A>g_B+n$. That is, the growth in abatement technology must exceed growth in aggregate output. Then the equation (14) can be rewritten:

$$\frac{\dot{E}}{E}=g_E+\alpha\frac{\dot{\tilde{k}}}{k}=g_E+\alpha s(1-\theta)k^{\alpha-1}-\alpha(g_B+n+\delta) \quad \text{with} \quad \frac{\dot{\tilde{y}}}{y}=\alpha\frac{\dot{\tilde{k}}}{k} \qquad (16)$$

The equation (16) can be illustrated diagrammatically as in Figure A.2.6. which show the condition for sustainable growth with $T$ as a emission turning point.

**Figure A.2.6: Sustainable emission growth**

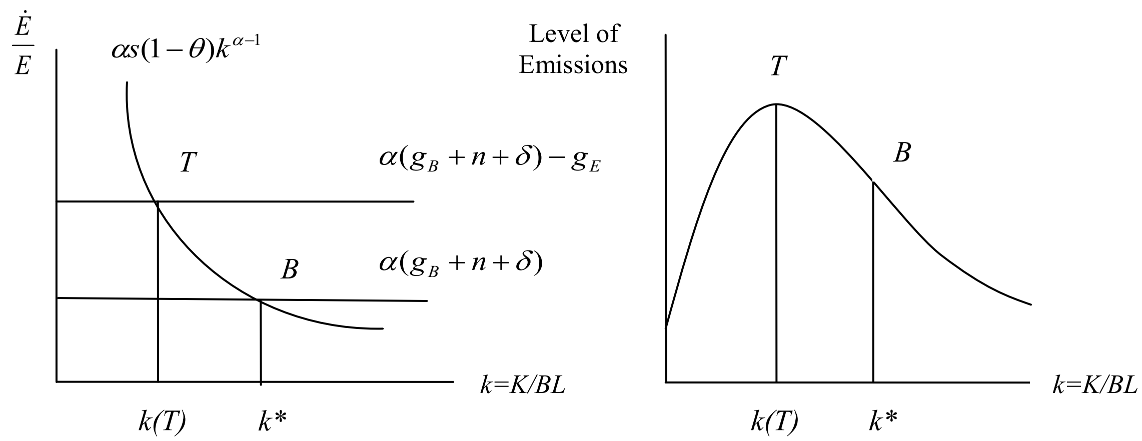



Figure A.2.6 shows the growth rate and the level of aggregate emissions for a case in which $g_E<0$. The model generates EKC hypothesis although the emission path over time depends on the initial point $k(0)$. That is, for $k(0)<k(T)<k^*$, the level of emissions grows at the beginning

and falls after $T$ (i.e. a hump-shaped EKC profile) due to exogenous technological progress in abatement, $g_E$. For $k(T)<k(0)<k^*$, emissions decrease for all times. See page 141 for comparative steady state analysis for the change in $s$, $\theta$, $g_B$ and $n$.

To derive the equation for convergence of emissions, the first step is to write the equation for emissions in per capita term, $e^c(t) = E(t)/L(t)$ as:

$$e^c(t) = \Omega(t)a(\theta)y^c(t)/[1-\theta] \qquad (17)$$

Where income per capita, $y^c(t)$, is given by $F(t)[1-\theta]/L(t)$. Differentiating with respect to time gives:

$$\frac{\dot{e}}{e} = -g_A + \frac{\dot{y}^c}{y^c} \qquad (18)$$

Approximating the growth rate of emissions and income by their average log changes over the period $N$ gives:

$$[1/N]\log[e_t^c / e_{t-N}^c] = -g_A + [1/N]\log[y_t^c / y_{t-N}^c] \qquad (19)$$

Using a log linearlisation obtained in Mankiw et al. (1992) for income convergence:

$$[1/N]\log[y_t^c / y_{t-N}^c] = b - \frac{1-\exp[1-\lambda N]}{N}\log[y_{t-N}^c] \quad \text{where } \lambda = [1-\alpha][n + g_B + \delta] \qquad (20)$$

and using $y_{t-N}^c = (1-\theta)e_{t-N}/\Omega_{t\text{-}N}a(\theta)$, a simple linear specification can be derived for emissions:

$$[1/N]\log[e_{it}^c / e_{it-N}^c] = \beta_0 + \beta_1 \log[e_{it-N}^c] + \mu_{it} \qquad (21)$$

where $\mu_{it}$ is the error term. For conditional convergence, the long specification is given by:

$$[1/N]\log[e_{it}^c / e_{it-N}^c] = \beta_0 + \beta_1 \log[e_{it-N}^c] + \beta_2 \log[s_i] + \beta_3 \log[1-\theta_i] + \beta_4 \log[(n + g_B + \delta)_i] + \mu_{it} \qquad (22)$$

## Appendix 2.7: Robust OLS Results

### Table A2.7.1: Robust OLS results, 1998/99-2003/04

**Total observation: 120 cross-section data from 1998/99 to 2003/04**
**Dependent variable: growth rate of recycling rate (log difference of recycling rate between 2003/04 and 1998/99)**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| **Constant** | 0.3777*** | 0.7500*** | 0.6244*** | 0.6039*** | 0.5320*** | 0.5910*** | 0.5109*** |
| | (0.0188) | (0.1300) | (0.1067) | (0.1056) | (0.1175) | (0.1185) | (0.1337) |
| **ln(Recycling1998)** | -0.1134*** | -0.1141*** | -0.1245*** | -0.1238*** | -0.1216*** | -0.1304*** | -0.1298*** |
| | (0.0086) | (0.0088) | (0.0073) | (0.0073) | (0.0072) | (0.0071) | (0.0069) |
| **ln(Earning)** | | -0.0375*** | -0.0048 | -0.0066 | -0.0000 | -0.0006 | 0.0043 |
| | | (0.0131) | (0.0114) | (0.0120) | (0.0134) | (0.0128) | (0.0132) |
| **ln(Density)** | | | -0.0260*** | -0.0258*** | -0.0261*** | -0.0209*** | -0.0196*** |
| | | | (0.0033) | (0.0033) | (0.0034) | (0.0034) | (0.0034) |
| **Women** | | | | 0.0687 | 0.1111 | 0.0580 | 0.0155 |
| | | | | (0.1363) | (0.1414) | (0.1329) | (0.1384) |
| **Education** | | | | | -0.0761 | -0.1303** | -0.1310** |
| | | | | | (0.0635) | (0.0653) | (0.0649) |
| **Unemploy** | | | | | | -0.6327*** | -0.5587** |
| | | | | | | (0.2393) | (0.2282) |
| **Ageover50** | | | | | | | 0.1231 |
| | | | | | | | (0.0932) |
| **$R^2$** | 0.602 | 0.631 | 0.743 | 0.744 | 0.746 | 0.765 | 0.768 |
| **Adjusted $R^2$** | 0.599 | 0.625 | 0.737 | 0.735 | 0.735 | 0.753 | 0.753 |
| **AIC** | -346.751 | -353.681 | -395.289 | -393.548 | -392.650 | -399.887 | -399.306 |
| **F-test for conditional convergence** | | 8.13*** | 38.72*** | 26.25*** | 20.62*** | 17.97*** | 15.14*** |

*Notes*: Standard errors are in parentheses. Significance is indicated by *, **, *** for 0.1, 0.05 and 0.001 level, respectively. F statistic tests the (joint) significant of a vector *Z* estimated in each regression.

**Table A2.7.2: Robust OLS estimation restuls, 2005/06-2008/09**

| **Total observation: 120 cross-section data from 2005/06 to 2008/09**<br>**Dependent variable: growth rate of recycling rate (log difference of recycling rate between 2008/09 and 2005/06)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **Constant** | 0.5214*** | 0.7309*** | 0.7985*** | 0.8790*** | 0.9198*** | 0.9018*** | 0.8923*** |
| | (0.0380) | (0.1046) | (0.1066) | (0.1669) | (0.1775) | (0.1775) | (0.1848) |
| **ln(Recycling2005)** | -0.1243*** | -0.1296*** | -0.1604*** | -0.1616*** | -0.1625*** | -0.1628*** | -0.1628*** |
| | (0.0114) | (0.0115) | (0.0167) | (0.0165) | (0.0169) | (0.0168) | (0.0168) |
| **ln(Earning)** | | -0.0191** | -0.0075 | -0.0080 | -0.0132 | -0.0114 | -0.0110 |
| | | (0.0090) | (0.0091) | (0.0091) | (0.0101) | (0.0107) | (0.0111) |
| **ln(Density)** | | | -0.0126*** | -0.0129*** | -0.0126*** | -0.0099* | -0.0095* |
| | | | (0.0047) | (0.0046) | (0.0046) | (0.0051) | (0.0055) |
| **Women** | | | | -0.1358 | -0.1317 | -0.1259 | -0.1371 |
| | | | | (0.2403) | (0.2457) | (0.2394) | (0.2425) |
| **Education** | | | | | 0.0398 | 0.0122 | 0.0100 |
| | | | | | (0.0602) | (0.0705) | (0.0717) |
| **Unemploy** | | | | | | -0.2491 | -0.2281 |
| | | | | | | (0.2298) | (0.2269) |
| **Ageover50** | | | | | | | 0.0268 |
| | | | | | | | (0.0857) |
| **$R^2$** | 0.4342 | 0.4521 | 0.4950 | 0.4969 | 0.5000 | 0.5063 | 0.5069 |
| **Adjusted $R^2$** | 0.4295 | 0.4427 | 0.4819 | 0.4794 | 0.4780 | 0.4801 | 0.4760 |
| **AIC** | -415.4676 | -417.3117 | -425.0997 | -423.5520 | -422.2873 | -421.8076 | -419.9529 |
| **F-test for conditional convergence** | | 4.49 ** | 5.66*** | 4.13*** | 3.21** | 3.02** | 2.61** |

*Notes*: See notes for Appendix Table A2.7.1

## Appendix 2.8: IV Estimation Results

### Table A2.8.1: IV estimation results, 1998/99-2003/04

| **Total observation: 120 cross-section data from 1998/99 to 2003/04** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Dependent variable: growth rate of recycling rate (log difference of recycling rate between 2003/04 and 1999/2000)** | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **Constant** | 0.4307*** | 0.7777*** | 0.6980*** | 0.6511*** | 0.5972*** | 0.5666*** | 0.6622*** |
| **ln(Recycling1998)** | -0.1323*** | -0.1329*** | -0.1396*** | -0.1381*** | -0.1364*** | -0.1318*** | -0.1325*** |
| **ln(Earning)** | | -0.0349** | -0.0142 | -0.0182 | -0.0133 | -0.0130 | -0.0188 |
| **ln(Density)** | | | -0.0165*** | -0.0160*** | -0.0163*** | -0.0190*** | -0.0206*** |
| **Women** | | | | 0.1564 | 0.1882 | 0.2157 | 0.2664 |
| **Education** | | | | | -0.0572 | -0.0291 | -0.0282 |
| **Unemployed** | | | | | | 0.3278 | 0.2395 |
| **Ageover50** | | | | | | | -0.1468 |
| **$R^2$** | 0.5434 | 0.5599 | 0.5899 | 0.5918 | 0.5927 | 0.5960 | 0.5986 |
| **Adjusted $R^2$** | 0.5396 | 0.5523 | 0.5793 | 0.5776 | 0.5748 | 0.5745 | 0.5735 |
| **AIC** | -280.7547 | -283.1476 | -289.6247 | -288.1817 | -286.4391 | -285.4277 | -284.2037 |
| **Speed of convergence** | 0.1883 | 0.1896 | 0.2043 | 0.2010 | 0.1972 | 0.1873 | 0.1888 |
| **F statistic for conditional convergence** | | 4.36** | 6.57*** | 4.54*** | 3.44** | 2.94** | 2.56** |
| **Jarque-Bera** | 11.43*** | 11.1*** | 26.27*** | 27.19*** | 25.49*** | 19.95*** | 16.29 |
| **Multicollinearity** | 0.4565501 | 0.4401389 | 0.4101193 | 0.40822012 | 0.4073454 | 0.40400325 | 0.40139903 |
| **Breusch-Pagan** | 9.02*** | 10.08*** | 9.57*** | 8.45*** | 9.00*** | 9.79*** | 9.44*** |
| **Ramsey RESET** | 0.69 | 0.75 | 0.70 | 0.71 | 0.71 | 1.19 | 1.24 |

*Notes*: See notes for Appendix Table A2.7.1. The speed of convergence is computed by $\lambda = -[(1/T)\ln(T\beta+1)]$. Jarque-Bera (JB) is a test for normality. The null is normally distributed error terms. Multicollinearity is examined using the Variance Inflation Factors (VIFs). The 1/VIF is the Tolerance which ranges from 0.0 to 1.0, with 1.0 being the absence of multicollinearity. Breusch-Pagan tests the null hypothesis that the error variances are all equal versus the alternative that the error variances are a multiplicative function of one or more variables. The Ramsey Regression Equation Specification Error Test (RESET) test (Ramsey, 1969) is a general specification test for the linear regression model, testing whether non-linear combinations of the explanatory variables have any power in explaining the exogenous variable. If non-linear combinations of the estimated values are statistically significant, the linear model is misspecified.

**Table A2.8.2: IV estimation results, 2005/06-2008/09**

| Total observation: 120 cross-section data from 2005/06 to 2008/09<br>Dependent variable: growth rate of recycling rate (log difference of recycling rate between 2008/09 and 2006/07) | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **Constant** | 0.3638*** | 0.5700*** | 0.6177*** | 0.5899** | 0.6061** | 0.5991** | 0.6238** |
| **ln(Recycling2005)** | -0.0815*** | -0.0867*** | -0.1084*** | -0.1081*** | -0.1084*** | -0.1085*** | -0.1083*** |
| **ln(Earning)** | | -0.0188 | -0.0106 | -0.0105 | -0.0126 | -0.0118 | -0.0128 |
| **ln(Density)** | | | -0.0089 | -0.0088 | -0.0086 | -0.0076 | -0.0086 |
| **Women** | | | | 0.0469 | 0.0485 | 0.0507 | 0.0798 |
| **Education** | | | | | 0.0158 | 0.0051 | 0.0110 |
| **Unemployed** | | | | | | -0.0966 | -0.1514 |
| **Ageover50** | | | | | | | -0.0697 |
| **$R^2$** | 0.1567 | 0.1712 | 0.1892 | 0.1894 | 0.1898 | 0.1906 | 0.1940 |
| **Adjusted $R^2$** | 0.1495 | 0.1571 | 0.1682 | 0.1612 | 0.1542 | 0.1476 | 0.1436 |
| **AIC** | -346.6658 | -346.7513 | -347.3803 | -345.4085 | -343.4687 | -341.5865 | -340.0913 |
| **Speed of convergence** | 0.0900 | 0.0952 | 0.1221 | 0.1218 | 0.1222 | 0.1223 | 0.1221 |
| **F statistic for conditional convergence** | | 2.05 | 2.32 | 1.55 | 1.16 | 0.95 | 0.86 |
| **Jarque-Bera** | 151.2*** | 147.2*** | 113.9*** | 113.3*** | 102.2*** | 111.7*** | 86.78*** |
| **Multicollinearity** | 0.84330569 | 0.8287761 | 0.81081643 | 0.81062605 | 0.81021972 | 0.80942444 | 0.8060269 |
| **Breusch-Pagan** | 4.35** | 6.84*** | 8.61*** | 8.71*** | 9.87*** | 8.97*** | 12.47*** |
| **Ramsey RESET** | 1.50 | 1.86 | 2.39* | 2.48* | 2.37* | 2.59* | 2.15* |

*Notes*: See notes for Appendix Table A2.8.1.

## Appendix 2.9: Estimation Results for the Entire Period

### Table A2.9.1: OLS estimation results, 1998/99-2008/09

| **Total observation: 120 cross-section data from 1998/99 to 2008/09** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Dependent variable: growth rate of recycling rate (log difference of recycling rate between 2008/09 and 1998/99)** | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **Constant** | 0.3226*** | 0.4667*** | 0.4172*** | 0.4093*** | 0.4198*** | 0.4385*** | 0.3874*** |
| **ln(Recycling1998)** | -0.0833*** | -0.0835*** | -0.0876*** | -0.0874*** | -0.0877*** | -0.0905*** | -0.0901*** |
| **ln(Earning)** | | -0.0145*** | -0.0016 | -0.0023 | -0.0033 | -0.0035 | -0.0004 |
| **ln(Density)** | | | -0.0102*** | -0.0102*** | -0.0101*** | -0.0085*** | -0.0076*** |
| **Women** | | | | 0.0266 | 0.0204 | 0.0036 | -0.0235 |
| **Education** | | | | | 0.0111 | -0.0061 | -0.0065 |
| **Unemployed** | | | | | | -0.2005*** | -0.1534** |
| **Ageover50** | | | | | | | 0.0784** |
| | | | | | | | |
| **$R^2$** | 0.8647 | 0.8761 | 0.9226 | 0.9228 | 0.9229 | 0.9279 | 0.9309 |
| **Adjusted $R^2$** | 0.8636 | 0.8740 | 0.9206 | 0.9201 | 0.9195 | 0.9241 | 0.9266 |
| **AIC** | -593.5802 | -602.1158 | -656.5440 | -654.8863 | -653.0925 | -659.1799 | -662.2497 |
| **Speed of convergence** | 0.1790 | 0.1802 | 0.2087 | 0.2071 | 0.2096 | 0.2354 | 0.2313 |
| **F statistic for conditional convergence** | | 10.74*** | 43.34*** | 28.84*** | 21.52*** | 19.83*** | 17.89*** |
| **Jarque-Bera** | 4.581 | 2.898 | 0.9175 | 1.207 | 0.9929 | 0.9057 | 0.9092 |
| **Multicollinearity** | 0.13528967 | 0.12391819 | 0.07743091 | 0.07721036 | 0.07707782 | 0.07205435 | 0.06907356 |
| **Breusch-Pagan** | 0.25 | 0.54 | 0.68 | 0.27 | 0.19 | 0.23 | 0.11 |
| **Ramsey RESET** | 0.77 | 1.09 | 1.80 | 1.89 | 1.94 | 0.97 | 0.67 |

*Notes*: See notes for Appendix Table A2.7.1 and Table A2.8.1. The explanatory variables for conditional convergence are observations in 2001.

**Table A2.9.2: IV estimation results, 1998/99-2008/09**

| Total observation: 120 cross-section data from 1998/99 to 2008/09<br>Dependent variable: growth rate of recycling rate (log difference of recycling rate between 2008/09 and 1999/2000) | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **Constant** | 0.3401*** | 0.4476*** | 0.4269*** | 0.4087*** | 0.4362*** | 0.4106*** | 0.4409*** |
| **ln(Recycling1998)** | -0.0883*** | -0.0885*** | -0.0902*** | -0.0897*** | -0.0905*** | -0.0867*** | -0.0869*** |
| **ln(Earning)** | | -0.0108 | -0.0055 | -0.0070 | -0.0096 | -0.0093 | -0.0111 |
| **ln(Density)** | | | -0.0043 | -0.0041 | -0.0039 | -0.0062* | -0.0067** |
| **Women** | | | | 0.0609 | 0.0446 | 0.0676 | 0.0837 |
| **Education** | | | | | 0.0292 | 0.0527 | 0.0530 |
| **Unemployed** | | | | | | 0.2744 | 0.2464 |
| **Ageover50** | | | | | | | -0.0466 |
| | | | | | | | |
| **$R^2$** | 0.6967 | 0.7012 | 0.7070 | 0.7078 | 0.7085 | 0.7152 | 0.7160 |
| **Adjusted $R^2$** | 0.6941 | 0.6961 | 0.6994 | 0.6977 | 0.6957 | 0.7001 | 0.6982 |
| **AIC** | -456.5901 | -456.3960 | -456.7464 | -455.0860 | -453.3563 | -454.1621 | -452.4798 |
| **Speed of convergence** | 0.1759 | 0.1769 | 0.1856 | 0.1830 | 0.1872 | 0.1684 | 0.1693 |
| **F statistic for conditional convergence** | | 1.77 | 2.04 | 1.46 | 1.15 | 1.47 | 1.27 |
| **Jarque-Bera** | 12.03*** | 14.15*** | 25.29*** | 25.00*** | 23.45*** | 14.55*** | 14.49*** |
| **Multicollinearity** | 0.30330483 | 0.29877453 | 0.29297959 | 0.29215159 | 0.29149428 | 0.28475762 | 0.28400482 |
| **Breusch-Pagan** | 5.32** | 6.56** | 6.46** | 5.86** | 5.33** | 5.55** | 4.97** |
| **Ramsey RESET** | 1.28 | 1.09 | 1.35 | 1.48 | 1.59 | 2.71** | 2.90** |

*Notes*: See notes for Appendix Table A2.9.1.

## Appendix 2.10: Top 20 Highest and Lowest Population Density and Relative Recycling Rates

**Table A2.10.1: 20 highest population density and relative recycling rates**

| Rank | Local authorities | 2005 | 2008 | Region | Authority type |
|---|---|---|---|---|---|
| 1 | Westminster | 0.74 | 0.64 | London | Unitary |
| 2 | Tower Hamlets | 0.36 | 0.54 | London | Unitary |
| 3 | Western Riverside Waste Authority | 0.86 | 0.76 | London | Disposal |
| 4 | Southwark | 0.59 | 0.58 | London | Unitary |
| 5 | Lewisham | 0.47 | 0.57 | London | Unitary |
| 6 | North London Waste Authority | 0.83 | 0.74 | London | Disposal |
| 7 | Merton | 0.89 | 0.84 | London | Unitary |
| 8 | Greenwich | 0.85 | 1.17 | London | Unitary |
| 9 | Luton UA | 0.96 | 0.96 | Eastern | Unitary |
| 10 | Sutton | 1.10 | 0.89 | London | Unitary |
| 11 | Kingston upon Thames | 1.02 | 0.98 | London | Unitary |
| 12 | Southampton UA | 0.91 | 0.77 | S East | Unitary |
| 13 | Leicester UA | 0.64 | 0.85 | E Midlands | Unitary |
| 14 | Croydon | 0.64 | 0.77 | London | Unitary |
| 15 | Nottingham UA | 0.77 | 0.90 | E Midlands | Unitary |
| 16 | West London Waste Authority | 0.87 | 0.93 | London | Disposal |
| 17 | Birmingham | 0.65 | 0.84 | W Midlands | Unitary |
| 18 | Slough UA | 0.75 | 0.71 | S East | Unitary |
| 19 | East London Waste Authority | 0.60 | 0.64 | London | Disposal |
| 20 | Reading UA | 0.83 | 0.96 | S East | Unitary |

**Table A2.10.2: 20 lowest population density and relative recycling rates**

| Rank | Local authorities | 2005/06 | 2008/09 | Region | Authority type |
|---|---|---|---|---|---|
| 1 | Northumberland | 1.20 | 1.08 | North East | Disposal |
| 2 | Cumbria | 1.12 | 1.17 | North West | Disposal |
| 3 | North Yorkshire | 1.20 | 1.20 | Yorkshire/Humber | Disposal |
| 4 | County of Herefordshire | 0.99 | 0.92 | W Midlands | Unitary |
| 5 | Shropshire | 1.33 | 1.32 | W Midlands | Disposal |
| 6 | Rutland UA | 0.96 | 1.47 | E Midlands | Unitary |
| 7 | Devon | 1.55 | 1.43 | S West | Disposal |
| 8 | Lincolnshire | 1.33 | 1.41 | E Midlands | Disposal |
| 9 | East Riding of Yorkshire | 0.96 | 0.94 | Yorkshire/Humber | Unitary |
| 10 | Wiltshire | 1.23 | 1.12 | S West | Disposal |
| 11 | Cornwall | 1.12 | 1.00 | S West | Disposal |
| 12 | Somerset | 1.60 | 1.36 | S West | Disposal |
| 13 | Norfolk | 1.34 | 1.19 | Eastern | Disposal |
| 14 | Dorset | 1.51 | 1.33 | S West | Disposal |
| 15 | North Lincolnshire UA | 1.04 | 1.36 | Yorkshire/Humber | Unitary |
| 16 | Sufflok | 1.62 | 1.34 | Eastern | Disposal |
| 17 | Cambridgeshire | 1.67 | 1.44 | Eastern | Disposal |
| 18 | West Berkshire UA | 0.79 | 0.94 | S East | Unitary |
| 19 | Gloucestershire | 1.17 | 1.16 | S West | Disposal |
| 20 | Durham | 0.82 | 0.81 | North East | Disposal |

## Appendix 2.11: Spatial Statistics

### Table A2.11.1: Moran's *I* (fixed distance and inverse distance weights matrix)

| | Fixed distance weight matrix | | | Inverse distance weight matrix | | |
|---|---|---|---|---|---|---|
| | 80 km | 100 km | 120 km | 80 km | 100 km | 120 km |
| **1998** | 0.420377 | 0.411090 | 0.308327 | 0.464659 | 0.411090 | 0.386828 |
| | (12.508004) | (13.062016) | (14.641332) | (12.046440) | (13.062016) | (13.997777) |
| **1999** | 0.361073 | 0.301126 | 0.287031 | 0.406140 | 0.368876 | 0.352997 |
| | (10.658456) | (11.748258) | (13.505860) | (10.439190) | (11.617273) | (12.657844) |
| **2000** | 0.362128 | 0.298594 | 0.285503 | 0.409100 | 0.371116 | 0.356094 |
| | (10.664776) | (11.625863) | (13.405752) | (10.490011) | (11.659910) | (12.737577) |
| **2001** | 0.303435 | 0.240162 | 0.228174 | 0.348517 | 0.312685 | 0.299716 |
| | (8.962695) | (9.399717) | (10.775587) | (8.955092) | (9.850753) | (10.752133) |
| **2002** | 0.307073 | 0.241190 | 0.219896 | 0.361821 | 0.327307 | 0.311333 |
| | (9.069963) | (9.441394) | (10.401626) | (9.291655) | (10.302407) | (11.160832) |
| **2003** | 0.198551 | 0.136258 | 0.132702 | 0.261526 | 0.227007 | 0.216448 |
| | (5.940685) | (5.463600) | (6.418954) | (6.763975) | (7.213123) | (7.836563) |
| **2005** | 0.140418 | 0.066956 | 0.046906 † | 0.178904 | 0.136283 | 0.116028 |
| | (4.276800) | (2.849430) | (2.518889) | (4.698903) | (4.438295) | (4.341586) |
| **2006** | 0.181211 | 0.105470 | 0.071177 | 0.240917 | 0.193909 | 0.165860 |
| | (5.450568) | (4.306836) | (3.625211) | (6.256307) | (6.207670) | (6.081954) |
| **2007** | 0.154304 | 0.104018 | 0.072362 | 0.211538 | 0.181622 | 0.157970 |
| | (4.677068 ) | (4.251871) | (3.679162) | (5.519010) | (5.830598) | (5.806510) |
| **2008** | 0.127923 | 0.079019 | 0.060048 | 0.181250 | 0.149466 | 0.132645 |
| | (3.913888) | (3.302303) | (3.114343) | (4.753111) | (4.837938) | (4.916562) |

*Notes:* The theoretical expected value is -0.008403 (= -1/n-2). *z*-scores are in parentheses. The critical *z* score values when using 90%, 95% and 99% confidence level are ±1.645, ±1.960 and ±2.574 respectively. All statistics are significance at 0.01% level except † indicating 0.05% significance level.

**Table A2.11.2: Getis-Ord General *G* (fixed distance and inverse distance weights matrix)**

| | Fixed distance weight matrix | | | Inverse distance weight matrix | | |
|---|---|---|---|---|---|---|
| | 80 km | 100 km | 120 km | 80 km | 100 km | 120 km |
| **1998** | 0.009457*** | 0.009355*** | 0.009288*** | 0.009407*** | 0.009311*** | 0.009229*** |
| | (7.195512) | (8.238250) | (7.910831) | (5.812213) | (6.335628) | (6.016049) |
| **1999** | 0.009281*** | 0.009238*** | 0.009201*** | 0.009151*** | 0.009311*** | 0.009047*** |
| | (6.119306) | (7.377898) | (7.269829) | (4.419380) | (6.335628) | (4.783902) |
| **2000** | 0.009180*** | 0.009130*** | 0.009114*** | 0.009070*** | 0.009011*** | 0.008966*** |
| | (5.881617) | (6.957110) | (6.976091) | (4.272533) | (4.694180) | (4.519348) |
| **2001** | 0.008872*** | 0.008838*** | 0.008835*** | 0.008725** | 0.008677** | 0.008641** |
| | (4.153975) | (4.857798) | (4.892295) | (2.405586) | (2.464933) | (2.213217) |
| **2002** | 0.008706*** | 0.008716*** | 0.008722*** | 0.008546 | 0.008529 | 0.008504 |
| | (3.112311) | (4.049783) | (4.138916) | (1.235397) | (1.305682) | (1.077469) |
| **2003** | 0.008469 | 0.008501 | 0.008517* | 0.008271 | 0.008273* | 0.008261* |
| | (0.858352) | (1.605536) | (1.838874) | (-1.456981) | (-1.724139) | (-1.908764) |
| **2005** | 0.008404 | 0.008435 | 0.008434 | 0.008188*** | 0.008198*** | 0.008188*** |
| | (0.004898) | (0.633091) | (0.618984) | (-2.943323) | (-3.360268) | (-3.572340) |
| **2006** | 0.008423 | 0.008437 | 0.008431 | 0.008264** | 0.008258*** | 0.008239*** |
| | (0.371212) | (0.813527) | (0.645537) | (-2.247981) | (-2.801234) | (-3.196585) |
| **2007** | 0.008389 | 0.008416 | 0.008422 | 0.008259** | 0.008269*** | 0.008259*** |
| | (-0.298869) | (0.337617) | (0.467556) | (-2.553059) | (-2.844566) | (-3.091103) |
| **2008** | 0.008385 | 0.008423 | 0.008438 | 0.008252*** | 0.008265*** | 0.008266*** |
| | (-0.400153) | (0.551338) | (0.924799) | (-2.815110) | (-3.083508) | (-3.076706) |

*Notes:* The theoretical expected value is -0.008403 (= -1/n-2). *z*-scores are in parentheses. The critical *z* score values when using 90%, 95% and 99% confidence level are ±1.645, ±1.960 and ±2.574 respectively. Significance is indicated by *, **, *** for 0.1, 0.05 and 0.001 level, respectively.

**Table A2.11.3: Moran's *I* (*k*-nearest neighbour weights matrix)**

| Year | *k*-nearest neighbour weight matrix | | | |
|---|---|---|---|---|
| | *k* =10 | *k* =15 | *k* =20 | *k* =25 |
| **1998** | 0.417535 | 0.333473 | 0.306964 | 0.284530 |
| | (11.974454) | (12.127908) | (13.331533) | (14.231404) |
| **1999** | 0.390778 | 0.293126 | 0.278680 | 0.262891 |
| | (11.098257) | (10.579190) | (12.003629) | (13.037085 |
| **2000** | 0.414912 | 0.314819 | 0.291169 | 0.267846 |
| | (11.742834) | (11.314991) | (12.498071 | (13.245882 |
| **2001** | 0.366109 | 0.275045 | 0.218138 | 0.190768 |
| | (10.374330) | (9.908686) | (9.438056) | (9.536789 |
| **2002** | 0.373656 | 0.277383 | 0.221548 | 0.192326 |
| | (10.586531) | (9.993364) | (9.582907) | (9.614183 |
| **2003** | 0.280841 | 0.198528 | 0.153268 | 0.122002 |
| | (8.002290) | (7.224837) | (6.727163) | (6.236432 |
| **2005** | 0.192349 | 0.136289 | 0.102883 | 0.072136 |
| | (5.560307) | (5.057466) | (4.635764) | (3.855912 |
| **2006** | 0.255606 | 0.178318 | 0.137133 | 0.099964 |
| | (7.314332) | (6.528265) | (6.064121) | (5.189590 |
| **2007** | 0.243470 | 0.173559 | 0.140472 | 0.101515 |
| | (6.978023) | (6.361802) | (6.203145) | (5.263829 |
| **2008** | 0.218619 | 0.139394 | 0.110510 | 0.080796 |
| | (6.281763) | (5.160992) | (4.948686 ) | (4.266422 |

*Notes:* See notes for Appendix Table A2.11.1. All statistics are significance at 0.01% level.

**Table A2.11.4: Getis-Ord General *G* (*k*-nearest neighbour weights matrix)**

| Year | *k*-nearest neighbour weight matrix | | | |
|---|---|---|---|---|
| | *k* =10 | *k* =15 | *k* =20 | *k* =25 |
| **1998** | 0.009282*** | 0.009155*** | 0.009048*** | 0.009015*** |
| | (4.457789) | (3.851802) | (3.311100) | (3.350757) |
| **1999** | 0.009062*** | 0.008925*** | 0.008924*** | 0.008962*** |
| | (3.404472) | (2.718705) | (2.720481) | (3.113837) |
| **2000** | 0.008962*** | 0.008811** | 0.008845** | 0.008897*** |
| | (3.106990) | (2.274209) | (2.465590) | (2.937082) |
| **2001** | 0.008662* | 0.008489 | 0.008496 | 0.008586 |
| | (1.655762) | (0.543907) | (0.587798) | (1.228010) |
| **2002** | 0.008501 | 0.008385 | 0.008377 | 0.008455 |
| | (0.709792) | (-0.135047) | (-0.190863) | (0.396119) |
| **2003** | 0.008255 | 0.008180** | 0.008181* | 0.008283 |
| | (-1.345400) | (-1.980991) | (-1.947817) | (-1.123942) |
| **2005** | 0.008162*** | 0.008180** | 0.008152*** | 0.008220** |
| | (-2.687142) | (-2.415630) | (-2.670654) | (-2.067833) |
| **2006** | 0.008219** | 0.008228** | 0.008169*** | 0.008225** |
| | (-2.403426) | (-2.213712) | (-2.902427) | (-2.338843) |
| **2007** | 0.008227** | 0.008234** | 0.008180*** | 0.008244** |
| | (-2.518705) | (-2.324044) | (-3.010760) | (-2.275993) |
| **2008** | 0.008249** | 0.008262** | 0.008229** | 0.008294 |
| | (-2.313184) | (-2.043695) | (-2.464232) | (-1.637341) |

*Notes:* See notes for Appendix Table A2.11.2.

# Chapter 3

# The Valuation of Landfill Disamenities in Birmingham

## 3.1 Introduction

Mounting environmental problems and a heightened environmental awareness have propelled policymakers towards more sustainable waste management practices based on the principles of re-use, recycling and energy recovery. The EU Landfill Directive (1999/31/EC) aimed to prevent and/or reduce the known negative effects on the environment arising from disposing of waste to landfills by introducing stringent technical requirements; and by setting targets limiting the amount of biodegradable municipal waste that could be disposed of by landfill. In order to divert waste away from landfill the UK Government introduced its Waste Strategy, setting national recycling targets and introducing regulations such as the Landfill Tax Escalator and the Landfill Allowance Trading Scheme (LATS).

However, the amount of waste appears ever-increasing and landfill remains the most prevalent methods of disposal in many parts of the EU, particularly the UK. There is continuing concern that the cost of disposing of waste through landfill is still priced at levels which fail to internalise the full social costs.

COWI report (2000) summerises different types of externalities arising from landfill disposal. First of all, emissions of landfill gas adversely impact both local air quality as well as exacerbating global environment problems. Biodegradable waste decays generating grrenhouse gases (GHGs). Both methane ($CH_4$) and, to a somewhat lesser extent carbon dioxide ($CO_2$), are potent GHGs contributing to climate change. In the UK, $CH_4$ emissions account for about 8% of the total GHG emissions in 2009 and landfill is one of the main sources, contributing 37% of total $CH_4$ emissions (DECC, 2011). In addition to $CO_2$ and $CH_4$, landfill gas contains trace gases and many different types of Volatile Organic Compounds (VOCs) such as benzene and vinyl chloride.

Water percolating through landfill results in leachate. The production and composition of leachate depends on the waste type accepted as well as the standard of construction of the landfill site. The co-disposal of hazardous and non-hazardous waste increases the toxicity of leachate in the process of biodegradation. Leachate can contaminate soil and groundwater, potentially impacting human health through drinking water and foodstuffs. Contaminants present in leachate also have detrimental effects on surrounding eco-systems. Increasingly the Government has prevented the mixing of hazardous and non-hazardous waste together in single landfill sites. Nowadays stringent regulations require the collection of leachate from landfill sites. Nonetheless, as long as there is significant rainfall, many landfill sites will continue to produce leachate through biological processes which could last for 30-40 years after closure (Robinson, 2005, p.1).

Responding to community concerns about the possible health impacts posed by landfill sites, a number of studies provide evidence that exposure to landfill emissions via contaminated air, water or soil can increase the risk of congenital anomalies and low birth weight (e.g. Elliott et al., 2001, 2009; Geschwind et al., 2004). Other studies by contrast fail to find any support for the presence of health risks associated with proximity to a landfill site (e.g. Marshall et al., 1997; Boyle et al., 2004).

Proximity to a landfill can also adversely affect individual welfare through nuisances like noise from site operation, visual intrusion, odour, dust, flies and the presence of vermin. Traffic to and from landfill may generate noise, air pollution, accident risks, traffic congestion and unwanted vibration. Collectively we shall refer to these nuisances as disamenity effects (although some would probably distinguish disamenity effects from actual health issues).

Disamenity effects may vary with the annual flow of waste as well as the accumulated stock of waste already landfilled. Furthermore, disamenity costs could vary across sites due to site management practices, the type of waste accepted, the number of years that the site has been in operation, or even prevailing wind direction.

Disamenity effects also include local residents' very perception of the health risks from landfill. Typically local residents are likely to have only partial or sketchy information on the health risks of living close to landfill sites. Consequently perceived risks and actual risks are unlikely to coincide (Cambridge Econometrics et al., 2003, p.3).

People's perception of landfills may depend on intangible impacts of landfill on the host community. This type of external cost, called stigma-related damages, can be attributed largely to the existence of hitherto unquantifiable or currently unimagined risks from landfill sites. Even if physical impacts from landfill are no longer a cause for concern, stigma-related damages can endure because a perception, once formed is likely to remain unchanged even after sites are closed or cleaned up (Guntermamnn, 1995, p.531).

Ignoring the fact that some landfill impacts are global, in an attempt to quantify the more local disamenity impacts of landfills previous studies have often used the hedonic price technique to evaluate the relationship between distance from the landfill site and the property prices. These disamenity impacts have furthermore been found to vary across studies mainly due to site-specific conditions of landfill such as the periodic quantity of waste sent to the landfill; the type of waste that the landfill is licensed to accept; the anticipated date of the landfill's closure; publicity about site contamination; and other 'announcement' type-effects. In the present study, therefore, incorporating such factors in hedonic regression analysis would facilitate the more accurate measurement of the disamenity effects of landfill.

In addition to those factors examined in previous literature, this study particularly focuses on two under-explored issues: longer term disamenity effects of landfill which persist even after site closure and the presence of multiple sites near to the property. Metropolitan areas may at any one time possess several active landfills and an even greater number of historical sites each potentially generating disamenity impacts. This implies that the presence of historical sites deserves more careful investigation and at the same time, the effect of historical site needs to be differentiated from that of active site.

Researchers however, have instead typically preferred to study smaller communities possessing only one landfill or have, in the case of larger communities possessing multiple landfills, assumed that only the nearest site has a disamenity impact on the price of property. And where researchers investigate the disamenity impact of multiple landfill sites this has invariably been within the context of studies using aggregate data (e.g. average house prices in a US county as a function of the annual quantity of waste sent to landfill) thereby implying significant loss of control in the hedonic price regression. This study by contrast tackles the 'standard case' in which properties are often simultaneously located close to more than one landfill sites, either active or, more frequently, historical.

Three models are developed with the intention of investigating these issues. The first model is a conventional model which focuses only on active landfill sites while considering various site-specific characteristics considered, such as the type of waste accepted and the number of operation years. The effect of downwind from active landfills is also taken into consideration. The second model examines whether there is any difference between disamenity effects of active and historical sites, how long negative externalities persist after closing and at what distance both active and former landfill sites stop affecting housing prices.

The last model deals with the existence of multiple landfill sites. As the disamenity impacts of landfill are believed to decay with distance, it has been typical to use distance from the nearest site as a proxy for landfill disamenity. While this measure may be appropriate for studies of houses with a single landfill site nearby, this fails to deal with a situation where houses are simultaneously located close to several landfill sites. As Elliott et al. (2009, p.81) pointed out in their epidemiological studies, distance to the nearest site gives equal weight of risks to houses living within the externality field of more than one site although landfill externalities may well be higher with greater density of landfill sites. Therefore, I use the number of landfill sites within a predefined distance from each house instead of distance to the nearest landfill to reflect the disamenity impact of landfill sites. I continue to draw the distinction between active and historical sites.

Combining Geographical Information System (GIS) data on landfill sites taken from the EA with the hedonic dataset of Birmingham collected for the study of noise pollution by Bateman et al. (2004) enables me to specify various landfill variables of interest. This combined dataset is by far the most sophisticated and largest hedonic dataset ever compiled for the study of landfill disamenities. The landfill dataset includes landfill site characteristics such as whether active or historical site, the type of waste accepted and the number of years operated in addition to site location from which we can extract data for distance and the bearing between houses and landfill sites. The dataset on the city of Birmingham contains 10,791 property sales matched with the abundant data on structural, neighbourhood, accessibility and environmental characteristics.

Using this dataset, the current study specifies landfill variables in an appropriate manner while also dealing with issues commonly encountered in hedonic price regressions, such as spatial dependence and market segmentation, in order to obtain a more accurate implicit price of landfill disamenities. This research effort is mainly motivated by a desire better to inform policy makers of the environmental cost of landfill and thereby provide part of the information necessary to develop an optimal waste management programme. More specifically, the optimal tax can only be set when accurate information on environmental damages is available. In the UK where the landfill tax is the main driver of landfill diversion, it is of particular importance to examine landfill disamenity impacts as one of environmental externalities associated with landfill disposal. The study of valuing landfill impacts furthermore make people more clearly aware of ever-growing costs of waste and landfill disposal. This will provides the basis for setting the correct level of the landfill tax and other preemptive taxes on waste generation.

To anticipate the main findings of the study, properties in Birmingham situated close to both active and historical landfill sites suffer a significant loss in value. However, active and historical sites appear to have distinctive features. For example, disamenity from active sites tends to vary with their characteristics. On the other hand, disamenity impacts from historical sites seem to vary only with distance, regardless of site-specific features.This study also finds that historical sites have a substantial impact on property values even 20 years after closure.

In addition, there is evidence of a strong association between property prices and the geographic density of landfill sites. However, the spatial boundary is different for active and historical sites. Quite apart from distance or density, the effect of being downwind of active landfill sites has a statistically significant impact along with the number of years operated.

The remainder of this study is organised as follows. In the second section, I provide an overview of the hedonic pricing method. In the third section, I review the empirical research dealing with the impact of landfill sites on property values. The fourth section describes the dataset used in the current study. Section five then discusses various alternative econometric specifications and presents the results. The last section concludes.

### 3.2 Hedonic Pricing Method

Rosen (1974) provides the first theoretical model of market behaviour for goods differentiated in terms of their characteristics, building on the "characteristics" approach to consumer theory forwarded by Lancaster (1966) in which utility is a function of the characteristics of goods consumed instead of the goods themselves, as in the traditional approach. The technique has been applied to explain the variation of the prices of agricultural goods, automobiles and wine products by their characteristics. Since there is no explicit price for each characteristic that characterises these goods, the hedonic method has been particularly useful in developing quality-adjusted price indices (Palmquist, 1999, p.765).

In environmental economics, hedonic models are extensively employed to estimate the willingness to pay for an improvement in environmental quality. The most common application is probably to air pollution but the technique has also been increasingly used for transportation noise and locally undesirable land uses such as landfill sites. The hedonic method has also often been applied to the labour market to estimate compensating wage differentials for injury risk.

Since Rosen's seminal contribution, the theoretical and empirical implementation of the model has been significantly improved and extended (e.g. Bartik and Smith, 1987; Epple, 1987; Palmquist, 1991). The hedonic technique is extensively discussed in Freeman (2003) and Hanley and Barbier (2009). In this section I review the basic theory of hedonic house price model and discuss some of the key issues raised in the literature.

In hedonic theory as applied to house prices, consumers consider a single house as one commodity, consisting of a vector of characteristics $Z$. This vector includes all structural characteristics of the property (e.g. the size, number of rooms and age of property), neighbourhood characteristics (e.g. wealth, ethnicity and demographic composition), accessibility characteristics (e.g. access to the city centre, parks and the freeway) and environmental characteristics (e.g. air quality and ambient noise levels). In sum, any house could be fully described by the vector:

$$Z = (z_1, z_2, z_3, ..., z_n) \qquad \textbf{(3.1)}$$

with $z_i$ the amount of the $i$th characteristic embodied in each house. In a housing market containing a continuum of housing characteristics, the price $P_j$, of a given house $j$, is determined by its vector of characteristics, $Z_j$, described by the hedonic price function:

$$P_j = P(Z_j) \qquad \textbf{(3.2)}$$

The exact relationship between a marginal change in any characteristic and the price of housing gives the implicit 'price' of that characteristic. This is illustrated in Figures 3.1(a) and (b). The horizontal axis is the quantity of a particular characteristic labelled $z_1$.

**Figure 3.1: The hedonic price and the implicit price schedules for characteristic $z_1$**

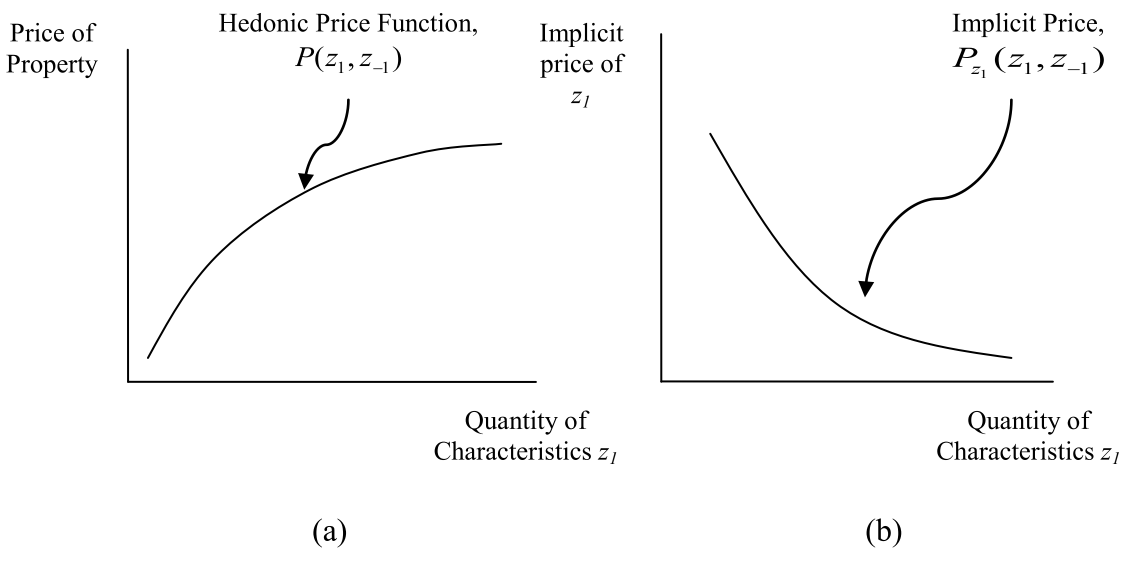



Figure 3.1(a) shows that the property price increases with the quantity of $z_1$ with other characteristics labelled $z_{-1}$ being held constant. In Figure 3.1(b), the marginal price of $z_1$ is

plotted. This can be derived by differentiating the hedonic price function with respect to $z_1$. The implicit price of characteristic $z_i$ is therefore:

$$P_{z_i}(z_i; z_{-i}) = \frac{\partial P(Z)}{\partial z_i} \qquad \textbf{(3.3)}$$

The hedonic house price equation is determined by the market interaction of demand and supply[45]. On the demand side, home buyers maximise their utility by selecting the optimal residential location. The household's utility is determined by the consumption of a composite commodity, $X$ with price equal to 1 and the vector of housing characteristics, $Z$: [46]

$$u = u(X, Z) \qquad \textbf{(3.4)}$$

The budget constraint is $M - P_j(Z) - X = 0$, where $M$ is income. The first order necessary condition with respect to any housing characteristic $z_i$ will determine the optimal quantity of that housing characteristic:

$$\frac{(\partial u / \partial z_i)}{\lambda} = \frac{\partial P(Z)}{\partial z_i} \qquad \textbf{(3.5)}$$

The ratio of marginal utilities on the left hand side defines the slope of indifference curve which gives the rate at which households are willing to give up money in order to acquire more of a housing attribute, $z_i$, whilst not altering their utility level. This ratio also defines the slope of household's bid curve (i.e. the marginal bid). The bid curve describes all the combinations of prices and level of an attribute that leave households at the same level of utility. Bid curves differ across households due to differences in income and other socio-

[45] The equilibrium hedonic price schedule for any particular housing market will be unique to that market reflecting the specific conditions of supply and demand that exist at that locality.

[46] It is assumed that the utility function presents weak separability and weak complimentarity. The first property implies that the marginal rate of substitution between two goods appearing in the utility function is independent of the quantities of all other goods consumed. The second property means that for zero purchase of differentiated goods, the MWTP for any characteristics is also zero (Hanley and Barbier, 2009, p.100).

economic factors.

The equation (3.5) gives the condition for the optimal choice of property for each household given that households maximise their utility by rethinking their house purchase decisions until the marginal bid is equal to the marginal cost or implicit price of an additional unit of $z_i$.

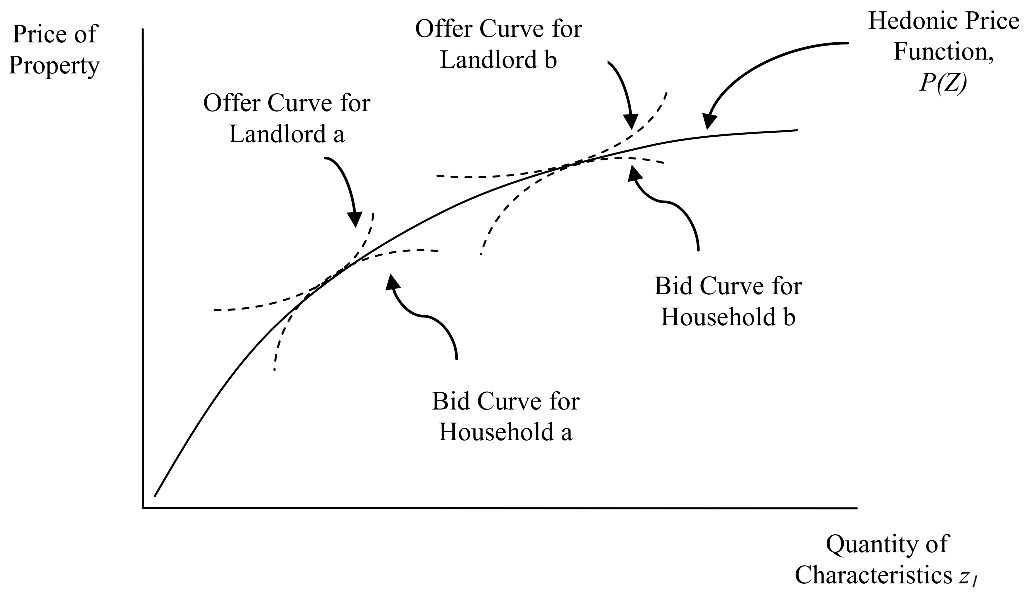
On the supply side, landlords have offer curves which describe all combinations of prices and levels of an attribute that leave landlords at the same level of profit. Such offer curves differ across landlords due to difference in exogenously given property characteristics and a number of other parameters including characteristics of each landlord.[47] In maximising profit, landlords would seek to provide a set of housing characteristics which gives them the highest level of profit while still compatible with reigning market prices. Similar to the optimal residential location for households, this entails a tangency condition that the slope of offer curve (i.e. isoprofit curve) is equal to the marginal implicit price for $z_i$.

As displayed in Figure 3.2, the main characteristic of the hedonic model is that households and landlords are efficiently matched along the hedonic price function if the market reaches the equilibrium for each attribute. In other words, the market will be in equilibrium when the hedonic price function, *P(Z)* is such that the aggregate market demand is equal to the aggregate market supply for properties with a vector of characteristics, *Z*. Each individual economic agent takes the equilibrium hedonic price schedule as given. Thus, the household's marginal willingness to pay (and landlord's willingness to accept) for a change in a housing characteristic $z_1$ is given by the implicit price of $z_1$ at any point along the hedonic price

[47] The amount of housing characteristics provided in the existing property market is assumed to be given exogenously. Such an assumption is fair at least in the short run since most housing characteristics are costly and time-consuming to alter and thus landlords have only a limited ability to change the attributes of the property. Thus the equilibrium price is completely determined by the demand side. Moreover, the use of disaggregate data in most of environmental economics allow less concern with the supply side. In other words, the housing market is competitive and individual home buyers cannot influence the hedonic price schedule (Palmquist, 1999, p.766)

function.

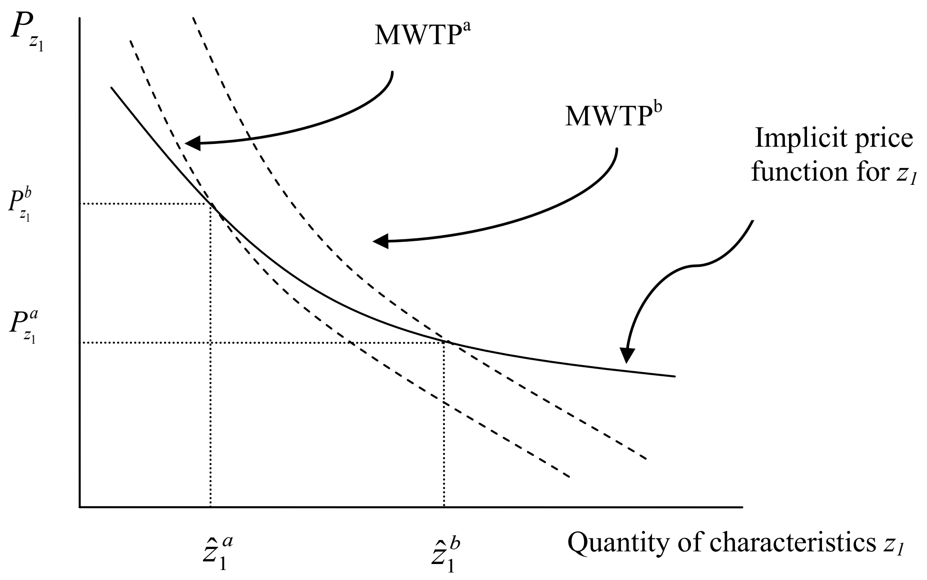
**Figure 3.2: Choice of property attributes for different households**




Estimation of the complete hedonic model consists of two steps. The first step involves estimating a hedonic price equation using appropriately informative property data which includes structural, neighbourhood, accessibility and environmental characteristics. The resulting parameter estimates can be used to infer the marginal benefit of a one-unit increase in each characteristic. At the equilibrium market price for each attribute, this requires that prospective buyers have information on all the alternatives available in the housing market, and that they are moreover able to adjust their consumption behaviour, moving along the implicit price curve until the each household's marginal willingness to pay (MWTP) for an increase in the characteristic is equal to the marginal implicit price.

Figure 3.3 shows the marginal valuation of an increase in $z_i$ to two households, *a* and *b* with different demand curves represented by $MWTP^a$ and $MWTP^b$ which decline with $z_i$ due to diminishing marginal utility. Each household maximises their utility by choosing the quantity of housing characteristic $z_1$ up to the very point where their MWTP is equal to the implicit price function. Thus, the implicit price curve observed can be used as a measure of benefits of a marginal increase in the attribute $z_1$ at the household's chosen location.

**Figure 3.3: Household choice of housing characteristics**




Some studies proceed to a second stage in which the marginal price obtained in the first stage is used to estimate the demand for individual attributes while taking into account demand shifters such as socio-economic attributes of households or the implicit prices of other nonmarket attributes. The second stage is particularly important when there is a significant change in the quantity of the nonmarket good and for which values based on marginal changes in the level of the characteristic no longer suffice.

However, the second stage faces difficult econometric problems: identification of the hedonic model and endogeneity of the marginal prices. The problem of identification arises because of the lack of information about the price that households are willing to pay for different levels of an attribute in addition to the prices and quantity observed. The literature often overcomes this problem by assuming the existence of segmented markets and then to use information on marginal implicit prices from these segmented markets to identify the demand curve (e.g. Palmquist, 1984; Boyle et al., 1999).

Secondly, it is difficult to estimate the demand equation as the price paid and the quantity of an attribute are simultaneously determined. Therefore, the second stage demand equation needs to be estimated using the IV method requiring truly exogenous variables and using them as instruments. These problems have led researchers to focus on the first stage of hedonic price model without carrying out the second stage for estimation of MWTP functions.

Numerous issues require to be addressed concerning the both the plausibility of the theoretical assumptions and correct empirical estimation of hedonic pricing models. I now review these issues insofar as they potentially impact on use of the technique for the purposes of uncovering the dismaneity impact of proximity to landfills.

Households should have full information on all housing prices and attributes. The implicit prices for each attribute are assumed to correspond to a market equilibrium in which supply equals demand and the existing stock of housing clears at the given prices. Moreover, utility-maximising home buyers exhaust all opportunities for possible improvements so that the marginal implicit price is always equal to their MWTP.

Unfortunately the assumption of perfect information is clearly violated. Furthermore, if there are significant transactions costs, households may not change their choice of attribute bundles in response to changes in prices, and the observed marginal implicit prices would diverge from the true MWTP for housing attributes. More generally a household’s optimal choice of property will not necessarily reflect their MWTP for housing characteristics with information costs, transactions costs and moving costs larger than the potential benefits associated with moving.

The hedonic model also assumes that all households make interior choices in their utility maximisation problem. Such an assumption requires that all characteristics have a smoothly continuous (differentiable) or concave distribution so that households can locate at a simultaneous equilibrium in all characteristics. However, if housing characteristics are not sufficiently varied or some units are not available at all, households may have to choose a house which does not fully satisfy the first-order conditions of utility maximisation. As a result, the marginal implicit price would not reflect the MWTP (Mäler, 1977, p.361).

Hedonic theory does not suggest a specific functional form for the hedonic price equation or provide a list of relevant housing attributes. Nevertheless, the choice of functional form may have a material impact on the estimation of implicit prices.

There may be instances in which prices should be a linear function of housing characteristics. This might occur when the characteristics of houses can themselves be separately supplied by competitive markets, e.g. the installation of double glazing and therefore enter the price functional additively. Parsons (1990) suggests that the price of property is a proportional to plot size (the 'repackaging' hypothesis). The implication is that locational attributes should be considered as public goods and weighted by lot size[48] (see Goodman, 1988 or Coulson, 1989). This is due to arbitrage activities in which competitive buyers untie and repackage bundles of attributes to exploit profit opportunity.

Despite these theoretical arguments, linear models are often taken as rather unrealistic and nonlinear specifications have been considered more appropriate. The semi-log and log-log forms are widely used in many hedonic studies. These two functional forms have an advantage in terms of reducing heteroscedasticity and other problems arising from the potential non-normality of the error term. Some studies have employed the Box-Cox

[48] While structural attributes, such as garage, bathroom and so on are confined to one household, locational attributes, such as air quality, access to local amenity and so on are provided at the same level to all the neighbouring households.

transformation (e.g. Cropper et al., 1988; Rasmussen and Zuehlke, 1990) which nests the logarithmic and semi-logarithmic functional forms as a special case. Instead of imposing an a priori structure on the functional relationship, researchers have also suggested semiparametric or nonparametric regression approaches for modelling hedonic price functions (e.g. Anglin and Gençay, 1996; Parmeter et al., 2007).

Market segmentation occurs when prevailing demand and supply conditions differ between markets, and buyers and sellers from one market do not participate in the market of any other location. Straszheim (1974) argued that urban areas in particular tend to have a series of separate property markets and that each market should have a different hedonic function. Fitting a single hedonic price function to data drawn from two or more segmented markets is tantamount to fitting a single regression function to what are essentially two or more spline functions. However, it is difficult to identify different market segments. In the literature, various criteria for market segmentation have been used e.g. economic, social, cultural and geographical aspects. The problem of heterogeneity over space can be addressed by allowing geographical variation in the underlying hedonic relationship across observations such that clusters of neighbouring observations assume similar implicit prices (see McMillen and Redfearn, 2010).

The cross sectional data used in hedonic house price analyses may exhibit spatial autocorrelation. This could occur if house prices are affected by the prices of neighbouring properties or if important omitted housing attributes are spatially correlated. Such spatial effects can be tested and modelled using different spatial process models. Pamlquist (1999) provides an overview of spatial econometric techniques used in hedonic studies.

Finally there is always a risk of biased estimates of implicit prices due to unobserved variables which are likely to be correlated with other explanatory variables, particularly in cross-sectional models (Greenstone and Gallagher, 2008, p.956). However, if we use as many explanatory variables as we can observe as potential determinants of property prices the hedonic price function is likely to suffer from multicollinearity or loss of efficiency (Freeman, 2003, p.363).

While the present study conducts as comprehensive analyses as possible by exploring many prominent issues in handling landfill disamenities as well as general issues in hedonic pricing studies, there can be some criticisms due to some inherited limitations of hedonic pricing methods. Above all, hedonic methods would not capture non-use values of environmental goods. To value non-use as well as use benefits, stated preference methods such as contingent valuation or choice experiments have been widely used for valuation. They involve asking individuals hypothetical questions which enable us to obtain a broader range of values.

In addition, as mentioned in Freeman (2003, p.393), the hedonic analysis only includes residential property but no other types of properties in urban areas, such as shopping centres and working areas. It is also noted that disamenity impacts captured largely depend on households' perception and thus the hedonic pricing method may not accurately measure the actual risks of living near landfill sites. Despite these considerations, the hedonic approach has a big advantage of valuing all possible environmental conditions of a house.

### 3.3 Literature Review

Empirical studies of landfill and property values typically invoke the hedonic price model. In total, 59 journal articles, working papers and dissertations were found with 'hedonic' and 'waste', using ECONLIT on 1st, June, 2010. In addition, articles were traced through references listed in earlier reviews. All papers available through the British Library and libraries of the University of Birmingham are reviewed. Most of these studies test the null hypothesis of no (negative) impact on property values arising from proximity to landfill. In addition, there have been a few studies which employed surveys to evaluate various household concerns about landfill.

This is not the first literature review dealing with the disamenity impact of landfill. Earlier literature reviews were carried out by Cartee (1989), Brisson and Pearce (1995) and Ready (2005).

Cartee (1989) summarises three of the earliest studies which show mixed results of landfill impact on property values. He concludes that such mixed results may be subject to factors like public perception on environmental risk, population density, site-specific characteristics and the nature of waste accepted.

Brisson and Pearce (1995) review both hedonic and contingent valuation studies on waste disposal sites such as landfills and incinerators. They present a simple meta-analysis of 11 hedonic pricing studies by regressing distance variable on a change in property values. The result indicate that house prices declined by 9% and 5.2 % within a 1-mile and 2-mile radius from landfill respectively.

Ready (2005) conducts a meta-analysis to estimate the effect on property values across landfills of different sizes, using the results on marginal implicit prices and varying features of 13 landfills studied in 9 articles. The estimation results provide strong evidence that the scale of landfill is significantly related to the size of disamenity effects. That is, prices increase by 5.92% per mile for high-volume landfills which accept 500 tonnes per day while it is 1.18% per mile for low-volume landfills.

There are other literature reviews which consider a broader range of contaminated sites, in addition to landfills (Farber, 1998; Jackson, 2001; Boyle and Kiel, 2001; Kiel, 2006; Simons and Saginor, 2006; Braden et al., 2009). [49]

In the following, I review both hedonic property value studies and non-hedonic property value studies. In the section of hedonic property value studies, I pay particular attention to the following: 1) whether or not landfill sites studied have a measurable effect on property values; 2) if there are landfill impacts, how the result changes over time, especially comparing before and after events like the discovery of contamination or National Priorities List (NPL)[50] nomination announcements and landfill closure; and 3) how the disamenity effects differ according to site-specific characteristics of a landfill or community

[49] Farber (1998) looks at 25 studies on undesirable land uses and provides summary estimates of these studies grouped by waste type accepted (hazardous, sanitary, chemical or nuclear). A summary for sanitary landfills shows that the estimate for increased property values per mile from sites range roughly from $7,000 to $14,000 which is higher than the impact of hazardous waste sites. However, such comparison may not be meaningful since the estimates are obtained from only a small number of studies.

Jackson (2001) reviews about 20 empirical studies which investigate the effect of environmental contamination on both residential and commercial property. His articles include hedonic regression analysis, case studies and reported appraisal outcomes. Particularly, he looks at two issues: the influence of remediation or closure of the site and any intervening influences, such as employment opportunities and whether the area is urban or rural. For residential property, there is strong evidence of adverse price effects from the source of contamination while such impacts are found temporary as they dissipate after remediation or closure. However, there is no conclusive result for the importance of intervening conditions while urban areas tend to experience higher house price discounts.

Simons and Saginor (2006) and Braden et al. (2009) also carry out a meta-analysis. Explanatory variables included in these meta-analyses provide guidelines for a systematic literature review. 58 studies on disamenity are reviewed, most of which are hedonic analyses but surveys, case studies and repeat sales analysis are also included. The following variables are estimated as determinants of a change in property values: unimpaired property values, distance to the source of contamination, dummies for types of source, information on contamination, closing or remediation, study methodology and other factors. The estimated coefficient on the distance variable is statistically significant and positive but a change in property values is negatively related to distance, which implies decaying externalities over distance. As expected, factors like the announcement of closing a site, a site in post remediation and large manufacturing plants are statistically significant and positively related to the diminution in property value while dummies for landfill, hazardous waste site and Superfund sites were insignificant.

The meta-analysis by Braden et al. (2009) is based on 46 studies on various types of waste sites. The following explanatory variables are investigated: geographical variables, types of sites, sample size, functional form, controlling spatial correlation, the inclusion of demographic and economic data and other variables. They find that property values declined by more than 10% within a 1-mile radius from the site. There is some evidence that NPL sites enjoy a smaller discount than non-hazardous sites, probably due to faster remediation actions taken.

[50] According to the passage of Comprehensive Environmental Response, Compensation and Liability Act (CERCLA) of 1980, the US Environmental Protection Agency (EPA) places potentially the most hazardous waste sites for human health and the environment on the National Priority List (NPL). Sites listed on the NPL are eligible for remedial response actions funded by Superfund established by CERCLA. The law was enacted after the famous Love Canal environmental disaster in the late 1970s

characteristics.

### 3.3.1 Hedonic Property Value Studies

A hedonic model for landfill disamenity impacts has been commonly estimated using multiple regression analysis or sales comparison between study areas and control areas. In such regressions, the relationship between proximity and property values has often been specified as nonlinear or discontinuous over different concentric zones. Inverse distance or distance squared has also been employed for capturing any nonlinear distance relationship. The literature review of empirical studies is organised as follows. Firstly, I review those studies dealing with the primary issue of whether the presence of landfill reduces property values, but without paying particular attention to more specific conditions related to each landfill site studied. These studies are reviewed chronologically but could equally be divided according to whether they find evidence for landfill disamenity impacts.

Then I review the literature which explicitly takes into account other potentially influential issues associated with landfill operation affecting the extent of disamenity impacts. These studies can be placed in one of several categories. One category deals with the impacts of households' perceived risk or knowledge about a landfill site adjacent to their property. The next category deals with the long term effects of landfill on property values that persist after site closure. Another strand of the literature attempts to show varying disamenity impacts depending on landfill characteristics such as the type or amount of waste accepted. Another group of studies focus on identifying different market segments based on housing structural and neighbourhood characteristics.

While hedonic studies generally employ micro-level data, there are also macro-level studies which estimate the density of landfill sites instead of distance to the nearest site. Such studies of macro-level data are often associated with the analysis of multiple landfill sites located near residential properties.

The earliest hedonic analysis of the disamenity impacts of landfill appears to be Havlicek et al. (1971, 1985). These studies examine 182 house sales observed around five solid waste landfill sites in Fort Wayne, Indiana, the US between 1962 and 1970. The estimated coefficient on distance in a pooled model shows that property values on average increase by 61 cents per mile from the nearest landfill. In addition to the distance variable, wind direction variable is included since odour, dust and strewn paper are carried out by the wind. The results show a $10.30 increase per degree away from downwind of the disposal site.

Some early studies observe property price appreciation and assume that the presence of a nearby landfill site is the cause. For example, the research in Goldberg (1972) (cited in Zeiss 1989a, p.66) considers the average change in property values over time as a measure of landfill disamenity effects without taking account of any other housing characteristic. The results show that visibility as well as proximity to landfill has negative effects on the appreciation of property values over time.

Adverse impacts of landfill are also detected in the study of Hockman et al. (1976) which estimate proximity to the nearest site as the only determinant of house prices. The study examines house sales that occurred in 1973 nearby 55 landfill sites in the Chicago Standard Metropolitan Statistical Area (SMSA). On average, property values decline by $60,500 per landfill site. In addition to distance to the nearest landfill site, the number of degrees that the house-site anlge is deviated from the prevailing wind direction also has positive impacts on adjacent property values.

Groth (1981) studies the rate of appreciation as well as price levels with regard to houses adjacent to five landfills in California, Oregon and Washington. This study concludes that landfill had a negative but only small impact on residential real estate. Petit and Johnson

(1987) show that properties near the Oaks Sanitary Landfill in Maryland experience up to 25% reductions in assessed tax value. However, the authors argue that the development of infrastructure such as roads and utilities around the landfill attracted new construction and that this might result in an offsetting increase in property values. As Farber (1989, p.4) notes, if a local disamenity enhances job opportunities, it may result in a price premium to properties in that area rather than depressing the prices. Therefore, such local conditions should be taken into account when interpreting the results from hedonic price models.

Instead of hedonic regression analysis, an alternative approach some of early studies employ is to compare a sales data of subject properties with comparable properties. The selection of comparable properties is based on the absence of adjacent landfill but the presence of other characteristics similar to subject properties. Such an approach is referred to as the sales comparison approach. Research and Planning Consultants, Inc of Austin, Texas (1983) study residential properties near to four landfill sites in Houston in Texas, Baltimore in Maryland, Minneapolis in Minnesota and Atlanta in Georgia. For each site, a comparable area is selected based on the similarity of structural and demographic characteristics, namely housing value, total number of housing units, percent of owner occupancy, owner ethnicity, household size, income and age of structures. The analysis takes two steps. Firstly, over a period of five years before and after opening the landfill, the mean residential sales values in the subject and control area are compared to analyse the effects of negative externalities from landfill. Secondly, the trend of the annual mean residential sales of the subject area before landfill development is used to predict the trend of the landfill's post-development period. If the predicted mean values are statistically significantly different from the realised values, this is evidence for the influence of landfill operation on the subject area. However, the difference between the actual and projected values is not statistically significant in most of the cases. This finding implies no impact of landfill or even an increase in the average values of properties in the subject areas compared to the control area. However, Cartee (1989) and Farber (1998) notes that this study was funded by Browning Ferris Industries, Inc (BFI), a major waste disposal contractor and thus, it is quite likely that BFI selected the study sites with anticipation of developing landfills.

Gamble et al. (1982) also find negative impacts of landfill. This study investigates Boyertown landfill in Montgomery County, Pennsylvania using data on 137 house sales within a 1-mile radius from the landfill between 1977 and 1979. The full sample shows an increase in house price of about 5% to 7% per mile at the 10% significance level. However, the estimation for each year shows statistically insignificant effects of landfill proximity on property values. Such results may be due to the small sample size and small range of distance from the landfill. The study also looks at property markets near ten sanitary landfills in Pennsylvania from 1977 to 1981 and shows the relationship between the volume of waste received and the rate of new residential construction or sales around each site. The results confirm that larger landfills appear to have bigger impacts in terms of reducing the rate of new construction and sales.

Price (1987)[51] compares appreciation rates of property values with property possessing a similar set of characteristics except landfill proximity. Landfills studied are located in Florida, New York and Manitoba, Canada. Since the entire region was experiencing a property value increase during the study period, the appreciation rate is more appropriate to compare instead of price levels. The results are somewhat mixed since some landfills in Florida and Manitoba do not seem to engender any impact on property prices. On the other hand, the remaining areas show statistically significant results and furthermore, indicate that the higher the property price, the smaller the impact of landfills on property values.

[51] Price (1987) also studies the impacts of thermal resource recover plants and transfer stations on property values and appreciation rates. None of them are found to have negative impacts on residential property values.

Bleich et al. (1991) point out the key weakness of early studies which only focus on comparing appreciation rates of subject areas and control areas. Those studies hypothesise that neighbourhoods near landfill sites experience lower appreciation. However, once the price level declines due to landfill operation, any subsequent change in appreciation rates may indicate the presence of long-term impacts of landfill disamenity on property values. For example, appreciation rates of subject areas will be higher than those of control areas if there is expected to be convergence at the end of operating life or negative externalities of landfill. If the long-term effect is permanent, appreciation rates of subject areas will be lower over time. Therefore, such studies need to be complemented by a study of changes in price level.

Greenberg and Hughes (1992) criticise previous studies for being idiosyncratic, investigating a single site or a single community. Thus they investigate 77 communities in New Jersey with Superfund sites and 490 without hazardous waste sites. They also compare appreciation in property values for communities with and without sites. Results suggest that communities with sites have a smaller increase in housing values than those without sites. In particular rural communities and communities with rapid increases in housing prices tend to experience bigger impacts of hazardous waste sites. In the following year, however, the findings of a survey conducted among tax assessors in New Jersey (Greenberg and Hughes, 1993) reveal that many sites do not lower the appreciation of property values but other factors, such as economic recession, local planning and high taxes have much more statistically significant effects on property values.

Nelson et al. (1992) estimate the price effect of an active landfill in Minnesota. In this research, a 2-mile radius is chosen as the outer limit for landfill impacts beyond which adverse effects from an active landfill studied disappear. Using 708 house sales sold in Minnesota between 1979 and 1989, the hedonic regression analysis shows that housing prices within 2 miles from the landfill experienced a 6% increase per mile from the site.

While Nelson et al. (1992) set a 2-mile radius as a boundary of landfill impacts, some studies attempt to identify the most appropriate radius as part of their regression analysis. Ready and Abdalla (2003) test a 1-mile and 2-mile radius as the spatial extent of landfill impacts with the index for landfill amenity impact (LFIND), constructed of the form:

$$\begin{aligned} \text{LFIND} &= 1/\text{distance} - 1/\text{K} \qquad && \text{if distance} \leq \text{K} \\ &= 0 && \text{if distance} > \text{K} \end{aligned} \qquad \textbf{(3.6)}$$

This allows testing a priori expectation about K as the spatial limit of landfill impacts. Indices for other local disamenities, such as airports, animal production and sewage treatment plants are constructed in the same way as for landfill. The area studied is Berks County in southeastern Pennsylvania and the data include 8,090 house prices between 1998 and 2002. Land uses are classified as agricultural and other open space use, residential use, commercial use and industrial use. Four adjacent landfills are classified as an industrial land use and a source of disamenities to adjacent residential properties. The results show that landfill disamenity impacts reach up to a 2-mile radius from landfill, reducing property values by 6.9% per 0.5 mile. Several other local disamenties are also statistically significant and have negative impacts on property values, such as a large-scale animal production facility and high traffic roads.

Arimah (1996) is the first paper which studies hedonic/landfill in developing countries. The studied landfill site is Achapo landfill in the city of Lagos, Nigeria. Historically, this landfill receives more than it can deal with thus causing significant deterioration of the surrounding areas. The analysis is conducted between October 1993 and January 1994. The hedonic regression results reveal that the annual housing rents within 3 km from the landfill increase by 9.4% per kilometre away from the landfill. The second stage of the hedonic analysis shows that annual income is an important determinant of the willingness to pay for improved sanitation. However, the distance-decay coefficient appears rather small compared to previous studies, probably due to the fact that the neighbourhoods studied are all low income.

Arimah and Adinnu (1995) take the further step of identifying three neighbourhoods as segmented housing markets adjacent to Achapo landfill. They find a statistically significant and positive relationship between distance to the landfill and house prices in one neighbourhood but an insignificant result and a significant but positive impact of landfill in the other two neighbourhoods. The authors speculate that the positive impact is due to a surge of migrants into a newly developed residential area in the neighbourhood.

Du Preez and Lottering (2009) also provide a case study in Africa. The studied area boundary is 2 km from a landfill located in Eastern Cape, South Africa. The proximity to the solid waste landfill reduces residential property values by 0.44% per 100 m.

In contrast to the studies reviewed so far, other early studies find no evidence of negative effects of landfill. Some of them even observe increased property values. However, this may largely due to the expected development of positive amenities in the study areas, perhaps as recompense for locating the landfill site within the community. For example, Schmalensee et al. (1975) study the value of residential properties adjacent to four sanitary landfills in Los Angeles County and find no evidence of landfill impacts on property values in most sites. Each site is separately analysed because of varying characteristics across sites. Only in one neighbourhood distance to the truck route shows the expected sign with the conventional level of statistical significance. Other landfill-related variables, such as proximity to landfill, degrees from prevailing wind direction and view of landfill from property, are either statistically insignificant or positively signed. However, it should be noted that there was the anticipated development of recreational sites, such as a golf course after closing the landfill.

Gamble and Downing (1984) study 9 sanitary landfills over a six-year time span. Four control areas around each landfill site are selected. In a pooled regression, a dummy variable is included indicating whether a property is located within 0.5 miles from the landfill. However, they too find no evidence of disamenity effects, a result possibly attributable to model misspecification due to the unwarranted assumption of uniformity of real estate markets adjacent to sanitary landfills. In addition, development of desirable land uses, such as a park and newly built expensive houses nearby the landfill may help to reduce negative externalities from landfill.

Zeiss and Atwater (1989a) study three host communities near Tacoma City landfill in Washington and include in the hedonic price regression various physical characteristics associated with landfills according to distance to landfill, view of landfill, odour arising, noise, air quality, water quality, accident risk and wildlife habitat. These variables are created using the facility's footprints. For example, groundwater and air quality deteriorates up to 1 km from the site while nuisances like odour and visual disamenity are observed up to 200-300 m from the landfill's boundary. The results show that only one of communities has statistically significant effects of explosion risk and air quality but they are positively related to property values. Housing prices of other two communities do not appear to have any relation with landfill impacts. The authors find a reason why surrounding property values increase, from the typical pattern of landfill location which is near to the urban fringe. As an urban area grows, its boundary is expanded to open and agricultural lands where landfills are often located. Although the distance to landfill decreases with urban growth, new home development may offset environmental impacts of landfill and raise property values.

Bleich et al. (1991) also find that there is no statistically significant effect of landfill disamenity. This study focuses on an existing landfill located in the San Fernando Valley in Los Angeles. One target area and two control areas are analysed using the hedonic price technique. The control neighbourhoods are selected on the basis of having similar characteristics in terms of ethnicity, family size and family income. The unexpected result may be attributable to the fact that the landfill site in question was well-designed and the local authority appropriately mitigated or countered potential impacts from the landfill.

Such inconclusive results have led to research which explicitly addresses potentially important factors influencing the extent of landfill disamenities. Several studies focus on the site-specific condition of landfills. In particular, they investigate the effect of information and knowledge regarding sites by comparing the existence or extent of disamenity impacts before and after adverse news such as a major toxic leak being discovered or designation as an NPL site (implying that the site is dangerous and must be cleaned up).

With increasing awareness of environmental issues in the wake of the discovery of hazardous waste sites such as Love Canal, the Environmental Protection Agency (EPA) funded some of the early hedonic studies looking at the environmental impact of NPL sites. Adler et al. (1982) and Cook et al. (1984) particularly attempt to distinguish the price effect of landfill on surrounding properties before and after the discovery of contamination. Two small communities, Pleasant Plains in New Jersey and Andover in Minnesota are studied, both of which are fairly homogeneous in terms of income and racial background. Pleasant Plains experienced contamination in wells as a result of illegal dumping and the incident was well publicised in 1974. Thus the Pleasant Plains data are divided into pre-1974 and post-1974 sales. The difference in price effects between these two periods would reflect the effect of public awareness of the contamination. Using data on house sales within a 2.5 mile radius from the Pleasant Plains site from 1968 to 1981, discrete distance variables for 11 concentric zones are estimated in separate models for the pre-1974 and post-1974 sample. The results show some evidence of a weak but positive relationship between housing prices and discrete distance variables after 1974, but no evidence of a relationship before 1974. Particularly, houses located between 1.5 mile and 2.25 mile away from the landfill are 6% to 11% more expensive than those located within 0.5 mile of the site. Although another study area, Andover in Minnesota, had fewer contaminated wells compared to Pleasant Plains, there was growing concern about future contamination of the site. Using data on house sales from 1978 to 1981, a continuous distance variable is used as a proxy for landfill impact in a pooled model. However, the distance variable is found statistically insignificant and had the wrong sign.

The dataset of Pleasant Plain is further expanded in Cook et al. (1984). Since the pre-1974 sample is too small for reliable results and both periods lack data on houses located beyond 2.5 miles from the site, new observations are added. The enlarged sample appears to improve the descriptive power of the estimations. Moreover, two alternative specifications are proposed to reflect the contamination of groundwater. The site is expected to have more pronounced impacts in the southwestern area due to the direction of groundwater flows. Thus dummies for direction and an interaction term between distance and a direction dummy are estimated in separate models. However, such a specification does not produce significant results for landfill impacts. The authors note that such results may be attributable to several factors like the collocation of other disamenities or amenities, the small sample size of houses close to the site, a consequence of government action immediately undertaken after contamination was discovered and the increasing popularity of the area due to the development of a nice new retirement community close to the site.

Michaels and Smith (1990) not only analyse the effect of information and knowledge of sites but also emphasise the importance of identifying each distinct housing market. They divide a sample of 85 towns in suburban Boston into four submarkets ranging from below average to premier according to structural and neighbourhood characteristics.[52] The hedonic regressions

[52] Michaels and Smith (1990) note that 82% of house sales involve realtors in 1981 according to the National Association of Realtors. With realtors' active participation in housing market, they are expected to be knowledgeable about specialised features of each segmented market. Thus the housing market of suburban Boston is segmented into four based on two realtors' classification.

for each market are run using data on housing sales prices for 2,182 single-family homes between 1977 and 1988. During this period, there are eleven landfill sites which are discovered to be contaminated at different points of time. Thus, in addition to the distance variable, two interaction terms between time dummies and distance are constructed. Time dummies are included as property sold within 6 months after discovery and after this 6-month period. In a pooled model for all submarkets, both distance and distance-time interaction terms have a positive sign and the latter terms are statistically significant. However, with market segmentation, only one of the submarkets shows statistically significant and positive interactive terms, and other submarkets show either statistically insignificant or a negative sign for landfill variables. In spite of mixed results, the benefits of removing a hazardous waste site from each submarket are calculated. Among submarkets, the premier market is the most sensitive to the presence of a hazardous waste site.

In the same vein, the importance of the extent and timing of public awareness is emphasised in Kohlhase (1991). Kohlhase estimates the parameters of a pooled cross-sectional model for 10 waste sites listed on the NPL during three distinct periods: before and after Superfund legislation in 1980, and after the announcement of being on the NPL in 1986. Using house prices within a 7-mile radius of the nearest site, the effect of distance to the nearest toxic site and its nonlinearity over distance are analysed for each of the three time periods. The results suggest no effect of legislation but a statistically significant and positive effect of distance to the site after the announcement of being on the NPL. In other words, home buyers are not aware of the potential risk associated with proximity to the toxic waste sites before the EPA announcement. Furthermore, a negative coefficient on the quadratic distance term suggests housing prices increase at a decreasing rate up to 6.2 miles (and decreased beyond that).

Smolen et al. (1992) compare disamenity effects of an active landfill site on property values each year. The site studied is a large toxic chemical waste landfill located in the Toledo

Metro area, Ohio. Since there was an ongoing debate about the question of the facility's long-term safety, the estimation of landfill impact over different time periods may show a change in public awareness about the site. The hedonic regression analysis takes two steps. First, a pooled model is estimated for three distance rings: 0-2.6 miles, 2.61-5.74 miles and beyond 5.75 miles from the landfill in order to identify the spatial limit of landfill impact. Real estate property values increase as the houses are located farther away from the landfill within the 0-5.75 mile range but decrease at distances greater than 5.75 miles from the landfill. Based on this result, the data are divided into two distance ranges, 0-2.6 miles and 2.61-5.74 miles from the landfill. Then separate hedonic regressions of each year, 1986, 1987, 1988, 1989 and 1990 are estimated for each distance range. Price effects over time do not change substantially year by year, ranging from a \$9,344 to \$ 14,205 increase per mile for houses within 2.6 miles from the landfill. This is probably due to its active status and continuing concerns about health risk around the site. Smolen et al. (1992) also examine disamenity impacts of a proposed low-level radioactive waste site in 1989. The immediate impact of the proposal on houses located within 2.6-5.75 miles is a \$4,160 reduction per mile. However, the adverse effect on property values disappears after the proposal is cancelled.

Wise and Pfeifenberger (1994) study a landfill in Uniontown, Ohio which accepts household rubbish, industrial liquids and sludge and other various solid wastes till 1980. The site was placed on the NPL in 1984 after the groundwater was found to be highly contaminated and a significant accumulation of methane gas was discovered. Subsequently, the EPA issued its plan for Superfund remedial cleanups of the site in 1990. The study period for the hedonic regression analysis covers the period of all these events from being operated to inactive status and designated as a Superfund site. However, the remediation was not undertaken during the study period. They find a decline of 10% in property values during the period of intensive publicity, 1987-1988, surrounding the problems of the landfill such as toxic water run-off and methane gas. However, the impact declines over time, recovering fully within 6 years. They conclude that landfill disamenity impacts on property values are temporary.

Reichert (1997) examines the same site in Wise and Pfeifenberger (1994). Reichert proposes an alternative way to compare landfill impacts over various events. He notes that negative news like discovery of a toxic leak would reduce the volume of sales transactions before a new lower market price is established. Such a liquidity effect is examined by comparing the volume of sales between the subject and control areas during the period, 1977-1991. The study shows that there is a temporary liquidity effect as property values in the subject area do not immediately fall to a lower level after discovery of contamination and thus the average marketing time for properties in the subject area is longer compared to control areas. However, the average marketing time becomes equal during the 1990-1991 period, once the housing market fully reflects the long-term impact of landfill. Afterwards the housing market adjacent to landfill experiences a permanent reduction in property values. In the hedonic regression analysis, a pooled model is estimated with sales prices a function of discrete distance variables for four concentric zones and interaction between yearly dummies and distance. The results show a significant effect of proximity to landfill on property values within the first three concentric rings (6,750 feet) from the site. The impact declines over distance, from 14.66% within 2,250 feet to 5.48% within 4,501-6,750 feet. In spite of the EPA's announcement on onsite remediation plan during the study period, property devaluation continues over the period. The presence of such a long-term stigma is at odds with the findings in Wise and Pfeifenberger (1994).

In 1999, Reichert replicates his early study with an extended time series. Although cleanup activities was not yet implemented, risk-reducing measures, such as city water supply to residents who used well water, taken during the study period is expected to minimise health risk and limit the negative impact of landfill on property values. Reichert includes a dummy describing whether the house is sold after the city starts to provide a public water supply to replace the groundwater. Compared to previous studies, the estimates obtained for each concentric zone appear slightly higher especially for later years. However, the effect of city water is negligible, particularly in the closest two concentric zones. This suggests that the effect of stigma outweighs the benefits of city water. With respect to the temporary or permanent nature of landfill impacts, Reichert (1999) examines a change in landfill impacts over different time periods using two alternative specifications. The entire period is divided before and after 1987 when intense publicity developed. The results on the distance and time-distance interaction term indicate a 0.6% decrease per foot closer to the landfill for houses sold after 1987. The post-1987 period is further divided into the 1988-1992 and 1993-1996 periods. However, there is no change in the magnitude of negative effects of landfill over these two periods, which supports the idea that stigma-related damages are permanent rather than temporary.

Some studies like Schulze et al. (1986) and Hite (1998) actively investigate the effects of information by including a variable indicating the depth of knowledge about landfill proximity or risk perception obtained through household surveys. In Schulze et al. (1986), the first part of the research investigates the effect of distance to landfill as a proxy for health risk. The study areas are three undisclosed landfill sites in California and each site is examined in a separate hedonic model. An inverse distance measure, as well as a dummy variable for properties located within 1,000 feet, is used as a measure of landfill disamenity impacts. Both variables show a statistically significant and negative effect on property values but only for one site, and either statistically insignificant or positive effects for the other two neighbourhoods. However, Schulze et al. (1986) note the fact that the public's perceived risk from landfill tends to be substantially larger than that provided by expert assessment. The second part of the research begins with a survey that assessed the level of risk residents faced from the landfill. The study area is a community adjacent to the OII landfill site located in the Los Angeles metropolitan area, California. This landfill accepts both municipal and hazardous waste before closing in 1983. During the operation, residents complain of odours, potential health risks and safety problems. The survey results show two distinctive features: 1) respondents believe the risk to be either very large or very small and 2) the judgment of risk is generally lower after closing the landfill. Based on the survey results, determinants of subjective risk beliefs are analysed in a regression model. In addition to the proximity to landfill sites, variables like the perception of odour, attitudes toward media attention and socio-demographic characteristics are included as explanatory variables. Interestingly, the results show that vivid cues from the site is the most important factor since a change in experienced odour explains most of the variation in perceived risk. Finally, survey results are used to construct a measure of the neighbourhoods' collective risk judgment and a hedonic model is developed to estimate the role of subjective risk on property devaluation. The regression analysis shows that the perception of health risk has a statistically significant effect and reduces house prices by $2,084 on average for a 10% increase in the proportion of neighbourhood respondents with high levels of risk perception. However, the distance to landfill is found statistically insignificant, probably because of multicollinearity with the perception variable. Furthermore, closing the landfill increases average house prices by $5,001. McClelland et al. (1990) summarise the latter part of the study in Schulze et al. (1986).

Hite (1998) uses survey data to explore the role of information about nearby landfill on property prices. Four landfill sites with varying life expectancies in Franklin County, Ohio are studied. A survey is conducted enquiring about individuals' knowledge regarding landfill proximity before purchasing their house. In order to examine whether knowledgeable buyers enjoy a larger discount than less knowledgeable ones the author estimates an equation where the dependent variable is the difference between asking prices and actual sales price as a percentage of the asking price. Furthermore, an interaction term between knowledge regarding the nearest landfill site and the log of distance to the site is included. The results show that both the dummy for knowledge and the interaction term have statistically significant effects on property values. Knowledgeable buyers living within 2.75 miles from the landfill get a discount of 10.65%.

Other studies of risk perception focus on the long-term effects of landfill on property values by estimating whether or not there is any residual loss in property values even after the closure of landfill. Arguably most of these losses are because of stigma-related damages rather than real risk.

An approach to estimate stigma-related damages taken by Guntermann (1995) is to compare the impact of open and closed solid waste landfills on surrounding property values. Twelve landfills are included in the study, two of which are refuse landfills and the rest are solid waste landfills. Damages from real risk are studied by distinguishing between refuse landfills and solid waste landfills (refuse landfills carry a lower risk of methane gas or groundwater contamination compared to solid waste landfills). Thus the impact of refuse sites would represent a direct estimate of the stigma component of damage while solid waste landfills without methane gas controls and groundwater monitoring systems would cause both real risk and stigma-related damages. A pooled model is estimated using 153 transactions of landfill itself as well as industrially zoned land near landfills in Phoenix, Arizona, from 1984 and 1994. In addition to dummies to identify properties located within the 1,000-foot boundary of a landfill, stigma-related damages are estimated using an interaction term between two dummy variables for open landfills and solid waste landfills. The results support adverse impacts of open and solid waste landfills on industrial properties but no impact of closed refuse landfills. Thus adverse price impacts from landfill are identified as temporary.

Furthermore, there is a bigger loss in value associated with the sales of landfills compared to other land transactions.

Halstead et al. (1997) study stigma-related damages from a small and inactive landfill in Belchertown, Massachusetts. This study aims at testing the implications of various functional forms for the hedonic house price regression. The regression results from the Box-Cox specification are compared with alternative ones, such as the linear specification with and without a quadratic term, and also the log-linear specification. None of the specifications uncovers an effect of proximity to landfill on house prices. Therefore, the study concludes that small and closed landfills have little bearing on property values as residents perceive that landfill disamenity impacts and risks disappear after site closure.

Skaburskis (1989) also studies the impact of a closed landfill site and focuses on identifying the boundary of landfill impact. The study uses a set of dummies for 8 concentric zones, ranging from 400 feet to 2,400 feet in 200 feet increments. The results indicate the presence of negative impacts from this landfill site. The 1,000 feet radius and 1,400 feet radius produce the most significant results.

Bouvier et al. (2000) compare the impacts of landfill sites in Massachusetts having varying sizes, operating status and histories of contamination. Of six landfill sites studied, two sites are open and the rest are either closed or inactive sites during the study period, 1992-1995. The boundary of landfill impact is set at 2 miles from the landfill. In separate site models, only one site which is relatively small and inactive shows a statistically significant and positive price effect for distance to landfill. The authors emphasise the fact that this landfill is on the EPA's potential threat list during the study period, which confirms information as a key determinant of people's risk perceptions. Particularly, when landfills are not visible in rural areas, information will have a crucial role in determining disamenities impacts on property values.

Hite et al. (2001) study the same sites as in Hite (1998) but focus on landfill life expectancy in order to investigate whether landfill impact is permanent or not. Using nonlinear three-stage least squares, the authors analyse a sample of 2,913 housing units sold in 1990 within a 3.25-mile radius from landfills. Landfill sites studied vary in life expectancy: two of the areas were closed for 6 years and 11 years respectively and the rest have a life expectancy of 2 years and 20 years respectively. Distance and its quadratic term are included for decaying externalities from landfill over distance. Market segmentation is achieved by including the proximity variables to each landfill site and interaction terms between a dummy variable for each site and all other explanatory variables, instead of separately estimating the hedonic price functions for each surrounding area. Furthermore, it is assumed that property taxes as well as rents are endogenously determined. Therefore, both the hedonic price function and the tax function are estimated. A variable for buyers' information is included, namely the percentage of households in a census block group that moved to their current location within the five years previous to 1990 from outside the state or the county. The results show that for all four landfill sites the proximity variables point to lower rents and taxes. Moreover, the price effects appear to increase with landfill life expectancy but at a decreasing rate over distance in general. The coefficient for information is statistically significant and positive, implying that individuals outside the area are likely to be less knowledgeable or have less reliable information about local housing markets.

Using a time series of house sales in a small community adjacent to a landfill in Pennsylvania, Kinnaman (2009) compares landfill disamenity impacts before and after the landfill was closed. The data covers 711 household units sold within a 1-mile radius from landfill, between 1957 and 2005. In a pooled model over the entire period, a continuous distance variable, a dummy for open status, and an interaction term of distance and open status dummy are included. He finds that the landfill has adverse impacts on property values no matter what status of the landfill. The estimated coefficient on distance implies that property values increase 34% per mile from the landfill. Thus the landfill site cast long-term stigma on property values.[53]

Another strand of the literature examines the effect of landfill characteristics, such as the type or amount of waste. Thayer et al. (1992) compare the disamenity impacts of hazardous and non-hazardous waste sites. The dataset includes 2,323 house sales taken from Baltimore city, Maryland, during 1985-1986 and 21 landfills and 16 hazardous waste sites. Variations in community characteristics include population density, ethnic composition, accessibility variables and school quality. Air quality is included along with water quality measured by direct access to the beach or pier. The results point to a statistically significant and negative impact of landfill on residential property values. Such results are robust to variations in functional form. As expected, the disamenity impact is significantly higher for hazardous waste sites. In the linear model the property price increases by $2,194 per mile from hazardous waste sites but by only $761 per mile from non-hazardous waste sites. Such a comparison between different types of landfills is also carried out by Baker (1982). Two municipal solid waste landfills and one industrial waste landfill are compared. Baker (1982) finds that the industrial landfill has a statistically significant and negative impact on property values but no effects from municipal waste landfills are detected.

Ready (2005) examines three active landfill sites of varying sizes in Pennsylvania from 1998 to 2002. Three 1-mile-wide concentric zones are tested. Two landfill sites show that the

[53] Long term effects from other types of undesirable land uses are investigated in Kiel and McClain (1995), Dale et al. (1999), McCluskey and Rausser (2003), Kiel and Williams (2007), and Greenstone and Gallagher (2008) by comparing housing market outcomes with a change in site status before and after opening or cleanup. McCluskey and Rausser (2003) and Kiel and Williams (2007) confirm the presence of long term effects of undesirable land uses as their results suggested that even cleanup activities did not fully eliminate previous losses in property values.

impact extends up to 2 miles and 3 miles respectively but there is no impact for the other site which is smaller and less visible. Distance to two landfills has a negative effect on property values.

Wang (2006) compares disamenity impacts across the same three sites analysed in Ready (2005) but includes spatial correlation of house price in hedonic pricing method. The study focuses on the most appropriate specification of spatial hedonic models (i.e. the spatial lag model, the spatial autoregressive (SAR) error model and the spatial error components (SEC) model). The study adopts the spatial limits for landfill impacts found in Ready (2005). The results of various spatial models confirm the existence of negative disamenity impacts from two out of three landfill sites, as in Ready (2005).

Lim and Missios (2007) compare on the size of disamenity impacts from two different landfills in Toronto, Ohio from 1987 to 1991. The boundary is set at 3 km from each landfill. Both combined and separate analyses indicate that the larger landfill depresses nearby property values to a greater extent.

Akinjare et al. (2011a) investigate disamenity impacts for four landfill sites in Lagos, Nigeria. The data are collected through surveying estate agents and surveyors, residents within 1.2 km of each landfill, and workers of Lagos State Waste Management Agency. In total, 2,341 survey responses, mostly from households are used but the study estimated separate regressions for each site as they differ in size, operating status and history. Within the hedonic framework, the reported asking price for houses is regressed on distance to the landfill and 24 other explanatory variables. The results confirm the downward impact of landfill proximity on property values while the size of the coefficients differs across the sites. The authors argue that the variation of disamenity effects across sites may be due to the nature of the soil around the site. Local conditions which affect demand for residential accommodation are also pointed out as a reason for variations. Overall, the study finds an average 6% increase in property values for households located more than 1.2 km from a landfill. Akinjare et al. (2011b) analyse the same data but compare the value of properties located within various concentric zones up to 1.2 km from the sites in 300 m steps. Across four neighbourhoods, it is revealed that property prices stabilise at 900 m from the nearest landfill.

Since Michaels and Smith (1990), the consequences of segmented housing markets have been discussed in several studies. Nelson et al. (1997) assumes that the housing market is segmented according to house values. In other words, higher valued homes may experience proportionately bigger price effects of landfill than lower valued homes. The hedonic model is applied to data on 644 house sales between 1977 and 1988 around a landfill in Eden Prairie, Minnesota. The results confirm the existence of a bigger disamenity impact of landfill on high valued houses. This suggests that the pattern of regional development would be influenced by landfill positioning as new landfills in the urban region are likely to attract low income households.

Zeiss (1984) analyses the disamenity impacts of landfill and incinerators with segmented housing market data. This study uses the price of property sold in 1982 around the Premier Street landfill in North Vancouver, British Columbia. The first segment consists of only condominiums and thus, their characteristics, in terms of things such as structure, age and size, are similar. Therefore, the author only includes the distance and the number of bedrooms as independent variables. Property values decline by 20% over the range between 120 m and 600 m from the landfill site. This is roughly consistent with the estimates of loss obtained from real estate agents and appraisers, which range between 15% and 25%. However, in the case of the other subdivision, the distance variable is statistically insignificant. The author notes that such results may be due to other varying housing characteristics of this area which are not properly taken into account in the statistical analysis.

Reichert et al. (1992) study the impact of five municipal landfills in Cleveland. First of all, residents living near the landfills are surveyed for information regarding perceptions of landfill impact. The survey data is then used to create indices of nuisance and health risk from landfill. These variables were both negatively correlated with house prices. A pooled model finds a statistically insignificant relationship between proximity to the landfill and property values, probably due to differences between the sites. With separate hedonic regressions coefficient estimates for the proximity to landfill are either insignificant or positive for each landfill. Only one area shows a statistically significant effect, reducing property values by $2,924. The study area is further reduced to a smaller and homogenous housing market surrounding the Westlake landfill. This is a newly developed area which is more expensive and occupied by younger residents. House prices within a 1-mile radius from the site experience 5.5% to 7.3% devaluation. Such results suggest that urban areas, more expensive houses and younger residents may be more sensitive to landfill.

Whereas most hedonic studies of landfill disamenities use micro-level data, some studies use a macro-level dataset. Ketkar (1992) used macro-level data for 64 municipalities in New Jersey. The dependent variable is median house prices for each municipality. The explanatory variable of chief interest is the number of hazardous landfill sites in each municipality. Results suggest that one more hazardous waste site decreases median house prices by 2%.

Brasington and Hite (2005) use a dataset containing the prices of 44,233 houses sold in 1991 in Ohio which is aggregated into 5,051 census block groups (CBGs). The housing market was segmented according to six metropolitan areas. In the year of the sample, there are 1,192 waste management contamination sites recorded as being potentially dangerous to human health or the environment. The distance to the nearest site is averaged over all the houses in the CBG. The distinctive feature of this study is that it addresses spatial dependence in the data. This is achieved by using the spatial Durbin model in which both spatially lagged dependent and independent variables[54] are included thus allowing spatial dependence through both the characteristics as well as the prices of neighbouring areas. Moreover, it also captures omitted variables that vary across space. The results point to a statistically significant and positive relationship between the distance to the landfill site and property values in five of the six housing markets. The coefficient on the spatial lag of house price is statistically significant and positive, which implies that house prices are positively related to the price of all other houses in the neighbourhood.

Notably, Ketkar (1992) takes into account the presence of multiple landfill sites in an area by estimating density instead of distance to the nearest site. The following stutides also deal with such a situation where residential properties are located near more than one landfill site.

In particular, the following two studies estimate both housing prices and wages while investigating the broad subject of contamination. For example, Blomquist et al. (1988) study various kinds of amenities and disamenities, including climate conditions, which vary across counties in New Jersey. The authors construct theoretical model where differences in amenities and disamenities are capitalised into house prices and wages and both need to be taken into account when calculating the implicit price. Hedonic housing and wage equations are estimated using a large micro-level dataset of houses in New Jersey from the 1980s. The total amount of waste licensed for landfills in county level is employed as a measure of landfill impact. The number of superfund sites and the number of treatment, storage and disposal facilities for hazardous waste in a county are also included. The effect of landfill is statistically significant but has a positive effect on both house prices and wages. The full

[54] For further discussion of spatial models, see the section 'spatial hedonic approach', pp.278-293.

implicit price for each environmental variable is calculated as the sum of the annual housing expenditure and wage differentials. Based on the implicit prices, a quality of life (QOL) index is constructed. The index indicates that individuals living in the county with the most amount of waste landfilled require an additional $1,410 compensation compared to those living in the county with the least amount of waste landfilled.

Likewise, Clark and Nieves (1994) also use both hedonic housing and wage equations to obtain the implicit value of eight categories of noxious facilities. The study utilises data from Public Use Microdata Sample (PUMS) of the 1980 Unites States Census which includes 45,899 owner-occupied house units, grouped into 76 PUMS study area. The sites studied include nuclear power plants, petrochemical refineries, coal-fired electric generating plants as well as chemical hazardous waste sites. Instead of distance, the disamenity impact from landfill is estimated using the density of each noxious facility per 1,000 square miles for each PUMS study area. The results show that the density of landfills has statistically a significant but positive effect on house prices. The impact on wages is found to be statistically insignificant. The authors suggested that home buyers are not fully aware of risk impact of hazardous waste sites before the sites are listed as Superfund sites.

Cambridge Econometrics et al. (2003) for DEFRA investigate landfill disamenity impacts in segmented property markets by county using housing and landfill data for England, Wales and Scotland. The study uses some 300,000 mortgage transactions between 1991 and 2000. Each house is matched with 7 property-specific variables and 40 socio-economic and neighbourhood variables at ward level. Landfill data include 5,828 sites in England and Wales and 1,300 landfills in Scotland, all of which were operational during 1993-1995.

This is the first hedonic study for the UK and deals with the case of multiple landfill sites by including variables measuring distance to the nearest landfill and the total volume of landfill surrounding each using zones of up to 0.5 miles, 0.5-2 miles and 2-3 miles around the house. Whereas distance to site is significant, the volume of landfill within the vicinity is not.

Overall, the results vary considerably across regions. For example, Scotland has the largest disamenity impacts from landfill, as 40%, 7% and 3% reduction in house value within 0.25 miles, 0.25-0.5 miles and 0.5-2 miles from landfill respectively. Elsewhere, West Midland and Wales display only 1.25% and 1.15% reduction within 0.25 miles. The loss of housing value across Great Britain as a whole is 7% within a 0.25 mile radius of the nearest landfill. Interestingly, landfill impacts reduce with the age of the landfill, possibly implying that households anticipate the closure of landfill sites. Table 3.1 presents a summary of the reviewed studies.

**Table 3.1: Empirical surveys of hedonic regression analysis**

| Authors and year | Landfill and location | Dependent variable | Independent pollution variables | Findings |
|---|---|---|---|---|
| **1.Havlicek et al. (1971, 1985)** | Five various solid waste landfills in Fort Wayne, Indiana | 182 house sales price (1962-1970) | -Distance from nearest disposal site<br>-The absolute degrees that the residential property is away from downwind of the disposal site<br>-Dummy for each disposal site | -61 cents increase in house price per foot( $3,220.8 increase per mile) from the landfill<br>-Positive effect of degrees away from downwind direction |
| **2.Schmalensee et al. (1975)** | Four landfills with various sizes in Los Angeles County | 61-447 house sales price and assessed values (1970-1975) | -Distance to nearest landfill (maximum distance ranges from 3431 to 7,290 feet (1.05 km-2.22 km))<br>-Truck noise (distance to truck route)<br>-View (dummy)<br>- The absolute degrees that the residential property is away from downwind of the disposal site | -Either positive or no effect of proximity and view of the landfill<br>-Negative effect of truck noise on property values in one site |
| **3. Adler et al. (1982)** | A contaminated site due to illegal dumping in Pleasant Plains, New Jersey | 675 house sales price (1968-1981) | 1.Dummy for 11 concentric zones up to 2.5-2.75 mile (4.02-4.43 km) for two datasets before and after contamination<br>2.Dummy for contamination zone set by government | 1. No effect prior to announcement but significant effect after announcement (6-11% more expensive price of houses located within 1.5-2.25 miles compared to those located within 0.5 mile)<br>2.Insignificant effect of contamination zone |
| | A solid waste landfill, Andover, Minnesota | 250 house sales price (1978-1981) | Distance to landfill within 2.5 mile (4.02 km) | Insignificant effect |
| **4.Gamble et al. (1982)** | A landfill in Montgomery County, Pennsylvania | 137 house sales price (1977-1979) | Distance to landfill less than 1 mile (0.61 km) | 1. $4,266 or 5-7% increase per mile for houses located within one mile from the landfill in a pooled model<br>2. Insignificant effect in regressions for each year |

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| **5. Gamble and Downing (1984)** | Nine sanitary landfills in Pennsylvania | 447 house sales price (1988-1981) | -Dummy for whether located within 0.5 miles (0.8 km) from the site or not<br>-Dummy for whether located near the main access road to landfills<br>-Dummy for control area | -Insignificant effects of proximity to landfill and control area<br>-Negative and weakly significant effect of main access road to landfill |
| **6. Zeiss (1984)** | A landfill in North Vancouver, British Columbia | 5,538 house sales price (1982-1984) | Distance to landfill (maximum distance is 1.2 km) | -20% increase for condominiums located between 120 m and 600 m from the site<br>-Insignificant effect on single family homes |
| **7.Cook et al. (1984)** | A contaminated site due to illegal dumping in Pleasant Plains, New Jersey | 1,350 house sales price (1968-1981) | 1.Dummy for 11 concentric zones up to 2.75 mile (4.43 km)<br>2.Dummy for contamination zone set by government<br>3.Dummy for four quadrants with the origin at landfill to reflect the effect of south-westerly direction of groundwater flow<br>4.Interaction between distance and dummy for four quadrants | Insignificant effect in all specifications |
| **8.Schulze et al. (1986) and McClelland et al. (1991)** | Three undisclosed landfill sites in 1984 in California | 50-185 house sales price (1983-1985) | 1.Dummy for whether located within 1,000 feet (0.3 km) from the site or not<br>2.Inverse distance to landfill | Positive and statistically significant effect only in one neighbourhood(($8828.86 reduction in house prices within 1,000 feet from landfill) and either positive or insignificant effect for the other two neighbourhoods |
| | A landfill closed in 1984 in Los Angeles, California | 178 house sales price (Aug 1983-Nov 1985) | An collective estimate of the neighbourhood's risk judgment | -$2,084 decrease in house prices per 10% increase in neighbourhood risk judgement<br>- $5,001 increase in house prices after closing the landfill |

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| **9.Blomquist et al. (1988)** | 1980 census data of US | 34,414 monthly expenditures on housing units (1980 census data) | -The number of superfund sites per county<br>-The number of treatment, storage and disposal facilities for hazardous waste and the number of water-pollution discharges per county<br>-The total licensed waste for landfills per county | Statistically significant but positive effect of landfill waste, Superfund sites, treatment, storage and disposal sites on both house prices and wages |
| **10.Zeiss and Atwater (1989a)** | Tacoma City landfill, Washington | 665 house sales price (1983-1986) | -Distance to landfill<br>-Other variables for facility impacts such as view, odour, noise, air quality, water quality, accident risk, wildlife habitat | - Insignificant effect |
| **11.Skaburskis (1989)** | Inactive landfill, closed in 1978 in Kitchener, Ontario, Canada | 214 house sales price (1985-1986) | -Dummies for six concentric zones up to 1,200 feet (0.37 km)<br>-Interaction between distance and dummy for each zones (with interactive term squared for quadratic model) | -$5,932 reduction in house prices and 11.9% increase per mile within 1,000 feet from landfill (linear specification)<br>-$12,590 reduction in house prices and the impact increases at a rate 43.18-0.058 × Distance (in miles) within 1,000 feet from landfill (quadratic specification) |
| **12.Michaels and Smith (1990)** | 11 various sized hazardous waste landfills in suburban Boston | 2,182 house sales price (Nov 1977- Mar 1981) | -Distance to nearest landfill (maximum distance = 13 miles (20.92 km))<br>-Interaction between distance and dummy for sales 6 months after discovery of the site<br>-Interaction between distance and dummy for sales after the end of this 6-month period | - Positive and statistically significant coefficient on interactive terms in a pooled model ($115 increase in house prices per mile from landfill)<br>-Mixed results for submarkets |
| **13.Bleich et al. (1991)** | A landfill in Los Angeles, California | 1,628 house sales price (1979-1988) | Dummies for two comparable neighbourhoods farther away from landfill (1-1.5 mile (0.61-2.41 km) and 3-6 mile (4.83-9.66 km) from landfill) | Insignificant effect |

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| **14.Kohlhase (1991)** | 10 NPL waste sites in Harris County, Houston | 1,083-1,969 house sales prices (1976-1985) | Distance and distance squared to the nearest toxic site within 7 miles (11.27 km) | Insignificant effect prior to Superfund status but $2,364 increase per mile for houses located within 7 miles from site afterwards (housing prices increase at a decreasing rate up to 6.2 mile) |
| **15.Reichert et al. (1992)** | Five municipal landfills in Cleveland, Ohio | 2,243 house sales price (1985-1989) | 1.-Distance to the nearest landfill<br>-Dummy for each site<br>2. -Distance to landfill<br>-Dummy for sales occurring at least one year after landfill opening<br>3.-Dummy for combined impact of landfill and railroad | 1.Insignificant effect<br>2.- Statistically significant but negative distance effect<br>- $2,924 or 6.1% reduction of the average price after landfill opening<br>3.$6,065 or 5.5% reduction in average house prices around landfill |
| **16.Ketkar (1992)** | Hazardous waste sites in 64 municipalities in New Jersey | 64 median value of properties (1980) | The number of hazardous waste sites in a municipality | $1,255-$1,600 or 2%-2.5% reduction in median values per one additional hazardous waste site in a municipality |
| **17.Smolen et al. (1992)** | A hazardous landfill site and a proposed landfill site in 1989 in Toledo, Ohio | 1,237 and 1,312 house sales price for each site (1986-1990) | 1.Distance to the existing landfill within 0-2.6 mile, 2.6-5.75 mile, greater than 5.75 mile (0-4.18 km, 4.18-9.25 km and over 9.25 km)<br>3.Distance to the proposed landfill within 0-2.6 mile, 2.6-5.75 mile, greater than 5.75 mile (0-4.18 km, 4.18 -9.25 km and over 9.25 km) | 1. $9,300-$14,205 increase per mile for houses located within 2.6 mile over the whole period but no effect on houses located 2.6-5.75 mile from landfill<br>2. $4,160 increase per mile within 2.6-5.75 miles right after the proposal but no effect after it was cancelled |

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| **18.Thayer et al. (1992)** | 21 landfills and 16 hazardous waste sites in Baltimore city and Baltimore county, Maryland | 2,323 house sales price (1985-1986) | 1.Distance to the nearest landfill<br>2.Dummy for four concentric zones from the nearest landfill, up to 5 mile (8.04 km)<br>3.-Distance to the nearest landfill<br>-Interaction between distance and dummy for hazardous waste sites | 1. $1,349 increase in house prices per mile from landfill<br>2. Decrease in price effects with distance from the landfill ($12,098 and $4.772 increase per mile within 1 mile and 3 miles from landfill respectively)<br>3. Bigger price effects for hazardous waste sites than non-hazardous sites ($761 and $2,194 increase per mile for non-hazardous and hazardous waste sites respectively) |
| **19.Nelson et al. (1992)** | A landfill in Ramsey Minnesota | 708 house sales price (1979-1989) | - Distance to landfill within 2 miles (3.22 km) | -6% increase per mile for houses located within 2 miles from landfill |
| **20. Wise and Pfeifenberger (1994)** | A toxic waste Superfund site in Uniontown, Ohio | house sales price (Jan 1977-May 1994) | - Distance to landfill | -10% reduction in house prices around landfill during 1987-1988 intensive publicity period<br>-House price recovery in 6 years since 1987 |
| **21. Clark and Nieves (1994)** | 76 PUMS study areas and 262 noxious facilities in the US | 45,899 annual imputed rent of owner occupied houses (1976-1980) | Density of various undesirable facilities per 1000 squares miles for each PUMS (hazardous waste sites, nuclear power plants, petrochemical refineries etc) | -Statistically significant but positive effects of hazardous waste sites on house prices<br>-Insignificant effect on wages |
| **22.Arimah and Adinnu (1995)** | A landfill in Lagos, Nigeria | 300 annual housing rent (Oct 1993-Jan 1994) | Distance to landfill within 3 miles (4.83 km) | Positive and statistically significant coefficient on distance only in one segmented market (0.174% increase per 1% change in distance for houses located 3 km away from the landfill) and either positive or insignificant effects for the other two segmented market |

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| **23.Gunterman n (1995)** | Ten solid waste landfills and two refuse landfills in Phoenix, Arizona | 153 sales price of industrially zoned land (1984-1994) | 1.Interaction between the open dummy and solid waste landfill dummy<br>2.Dummy for sales of solid waste landfills<br>3.Dummies for whether the whole, 50% or less than 50% of area is within 1,000 feet of the site<br>4. Interaction between the solid waste dummy and a dummy for methane gas controls and groundwater monitoring | 1. 45% reduction in land values around open and solid waste landfills<br>2. 51% reduction for sales of solid waste landfills<br>3. Insignificant effects<br>4. Insignificant effects |
| **24.Arimah (1996)** | A landfill in Lagos, Nigeria | 300 annual housing rents (Oct 1993- Jan 1994) | Distance to landfill within 3 km | 9.4% increase per kilometre for houses located within 3 km from landfill |
| **25.Halstead et al. (1997)** | A small and inactive landfill in Belchertown, Massachusetts | 103 house sales price (Jan 1992- Aug 1995) | Distance to landfill within 2 miles (3.22 km) | Insignificant effect |
| **26.Nelson et al. (1997)** | A landfill in Eden Prairie, Minnesota | 644 house sales price in 1980 constant dollars (1977-1988) | Distance to landfill within 3 miles (4.83 km) | -8.83% increase per mile for houses within 3 mile from landfill<br>-Bigger price effects of landfill for higher valued homes |
| **27.Reichert (1997)** | A toxic waste Superfund site in Uniontown, Ohio | 1,394 house sales price (Jan 1977-May 1994) | -Dummies for four concentric zones up to 9,000 feet (2.74 km)<br>-Interaction between yearly dummies and a dummy for each zone | - Decrease in price effects with distance from the landfill (14.66%, 6.4% and 5.48% reduction in the average house prices within the first three distance rings)<br>-No change in the price effect of landfill over time |

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| **28. Hite (1998)** | Four landfill sites in Franklin county, Ohio | 487 (asking price-sales price)/asking price (1991) | 1. Log of distance to landfill within 3.25 mile (5.23 km)<br>2.-Dummy for knowledge of landfill<br>-Interaction term between knowledge and the log of distance | 1.Insignificant effect<br>2.10.65% more discount per mile for knowledgeable buyers compared to unknowledgeable buyers |
| **29.Reichert (1999)** | A toxic waste Superfund site in Uniontown, Ohio | 1,029 house prices (Jan 1977-Sep 1996) | 1.-Dummies for four concentric zones up to 9,000 feet (2.74 km)<br>-Interaction between yearly dummies and a dummy for each zone<br>2.-Distance to outer limit of 9,000 feet (2.74 km)<br>-Interaction between distance and dummy for sales occurring after intensive publicity in 1987<br>3.-Interaction between distance and dummy for sales of 1988-1992<br>-Interaction between distance and dummy for sales of 1993-1996 | 1. Decrease in price effects with distance from landfill but overall increases in impact compared to Rechert et al. (1997) (14.56%, 7.26% and 5.80% reduction in average house prices within the first three distance rings)<br>2. Approximately 0.9% and 0.6 % decrease in house price per foot closer to the landfill over the whole period and after 1987 respectively<br>3. No change in the magnitude of negative effects of landfill over the two periods |
| **30.Bouvier et al. (2000)** | Six landfills in central and western Massachusetts | 385 sales price (Jan 1992- Aug 1995) | Inverse distance to landfill within 2 miles (3.22 km) | Negative and statistically significant at the ten percent level coefficient on inverse distance only for one landfill site (6% increase per mile) and insignificant effects for the rest of the sites |
| **31.Hite et al. (2001)** | Four open and closed landfills in Franklin County, Ohio | 2,913 house sales price (1980) | Distance to landfill and distance squared to each landfill within 3.25 mile (5.23 km) from landfills | -Negative effect of both open and closed landfill on house prices<br>- Increase in price effects with landfill life expectancy<br>- Decrease in price effects with distance from landfill |

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| **32.Ready and Abdallah (2003)** | Four landfills in Berks County, Pennsylvania | 8,090 house sales price (1998-2002) | -An index of the landfill amenity impact (LFIND=(1/Distance)-(1/K) if Distance<K otherwise LFIND=0, K ranges up to 2.4 km)<br>-Indices for other local disamenities: airports, mushroom production, large-scale animal production, sewage treatment plants and high-traffic roads | -The largest effect of landfill among local disamenities<br>-Decrease in price effects with distance from landfill (12.4%, 6.9%, 3.8% and 0.8% reduction in house prices within 0.5 km, 0.8 km, 1.2 km and 2.4 km respectively from the nearest landfill) |
| **33.Cambridge Econometrics et al. (2003)** | 5,828 landfills in England, Wales and 1,300 landfills in Scotland, operational in 1993/94 and 1995 respectively | 332,940 house sales price, ranging from 25-17,566 observations across counties (1991-2000) | -Distance to nearest landfill<br>-Aggregated landfill area/volume within 0.5 mile, 0.5-2 mile and 2-3mile from a house (0.8 km, 0.8-3.22 km and 3.22-4.83 km) | -Results vary across counties<br>-Comparison of residuals with different types and distances from landfill sites reveals that Scotland had the largest disamenity effects from landfill (40%, 7% and 3% reduction in house value within 0.25 mile, 0.25-0.5 mile and 0.5-2 mile from landfill) |
| **34.Brasington and Hite (2005)** | 1192 sites in Ohio, on a Master Sites List in 1994 | Average house sales price of 550, 911, 1580 and 872 CBG for each metropolitan city (1991) | Log of average distance to the nearest site (maximum distance = 1.69-2.22 mile (2.72-3.57 km)) | 0.029% increase in average house price of CBG per 1% change of the average distance from the nearest site |
| **35.Ready (2005)** | Three landfills in Berks County, Pennsylvania | 11,069 house sales price (1998-2002) | 1. Dummy for three concentric zones up to 3 miles (4.83 km)<br>2. Distance to each landfill within 2 miles and 3 miles (3.22 km and 4.83 km) | 1. Significant effect within 2 and 3 miles for two large-scale landfills but insignificant effect for the smallest landfill within all three zones<br>2. 7.21-10.86% increase in house prices per mile from the two large-scale landfills and insignificant effect for the smaller landfill |

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|---|---|---|---|---|
| **36.Wang(2006)** | Three landfills in Berks County, Pennsylvania | 11,069 house sales price (1998-2002) | -Distance to each landfill within 2 miles and 3 miles (3.22 km and 4.83 km)<br>-Spatial effects using the spatial lag, SAR error, SEC model. | Significant effect within 2 and 3 miles for two large-scale landfills but insignificant effect of the smallest landfill within all three zones |
| **37.Lim and Missios (2007)** | A large-scale landfill and a small local landfill in Toronto, Canada | 331 and 1139 house sales price for each landfill (1987-1991) | 1.Distance to landfill within 3 km in separate site regressions<br>2.-Distance to landfill within 3 km<br>-Interaction between distance and dummy for a large-scale landfill | 1. CDN$5.4 and CDN$3.15 increase per mile from large scale and small-scale landfill, respectively.<br>2. CDN$9.8 and CDN$3.1 increase per mile from large scale and small-scale landfill, respectively. |
| **38.Kinnaman (2009)** | A landfill closed in 1976 in Lewisburg, Pennsylvania | 711 house sales price (1957-2005) | -Distance to landfill (maximum distance=1.3 mile or 2.1 km)<br>-Dummy variable for landfill in open status<br>-Interaction between distance and dummy for landfill in open status | -34% increase in house prices per mile from landfill<br>-Insignificant effect of closing landfill<br>-Insignificant effect of proximity to landfill in open status |
| **39.Preez and Lottering (2009)** | A closed landfill in New Brighton, the Nelson Mandela Metropole, South Africa | 496 house sales price (2005) | Distance to landfill within 2 km | 0.44% increase per 100 m for houses |
| **40. Akinjare et al. (2011a)** | Four landfills in Lagos, Nigeria | 2341 asking house prices | Distance to each landfill within 1.2 km | Significant effect across all sites (4-7% increase in house prices for 1.2 km away from landfill) |

*Notes*: 1 mile=1.61 km. The numbers in the table refer to different models and the bullet points refer to proxy variables for landfill impact. When a boundary was not set for house sales observations from the edge of landfill studied, the maximum distance from landfill to property is given in the table. PLUM: Public Use Microdata Sample from the 1980 Unites States Census.CBG: Census Block Group.

### 3.3.2 Non-hedonic Property Value Studies

There are also studies which used contingent valuation or survey methods to investigate the relationship between household attitudes towards landfill and property devaluation. For instance, Swartzman et al. (1985) conduct a survey which asks how close to a hazardous waste landfill people are willing to live given compensation, such as property tax relief or a user fee paid by landfill operators and risk reduction through increased monitoring and increased control over monitoring by local community. The selected community is a rural area of Illinois County which does not have any waste disposal facility. 105 participants from eight different backgrounds answered the questionnaire. Non-parametric statistics are employed to assess whether changes in willingness to live closer are statistically related to the level of compensation and risk reduction efforts. The study reports that there is a statistically significant increase in the number of people willing to live closer as the level of compensation increases. For example, given no reduction in property taxes, nearly 60% of the respondents prefer to live over 50 miles away from a landfill. However, with 75% tax relief, only 25% remains of the same opinion whereas the rest are willing to live closer to the landfill. This study suggests that strong opposition to hazardous waste facilities by local communities can be reduced through offering compensation.

Smith and Desvousges (1986) aim at estimating the demand for distance from a hazardous waste disposal site. A survey of households is conducted in suburban Boston in 1984. In the survey, two houses are presented with different distance to a hazardous waste site but identical in all other characteristics. The price of the house is increased by \$250, \$600, \$1,000 and \$1,300 and randomly assigned to each respondent. Then, individuals are asked which house they preferred to purchase. The results indicate that the consumer surplus of the average household increases by between \$330 and \$495 annually per mile from the landfill site. With the growing difficulties of siting such facilities due to opposition by local communiies, such empirical estimates help Government understand the source of homeowners' resistance and better design a compensation programme.

Survey results in Zeiss and Atwater (1989b) show that monetary compensation would not be enough to win public acceptance of waste disposal facilities. They suggest that property-value guarantees (PVGs) would alleviate the problem of negative economic externalities from landfill. Property-value losses are assessed as the difference between sales price and fair market value. However, a representative survey conducted for a hypothetical landfill and incinerator indicates that although nearly 50% of respondents consider PVGs as fair compensation for their losses from facility siting, it is still necessary to take measures to mitigate the primary impacts from the facility, such as health and nuisance impacts.

Furuseth (1990) reports the results of a survey carried out in the residential communities surrounding the Harrisburg Sanitary Landfill in Charlotte, North Carolina, US. A hundred residents living within a 4,800 m perimeter of the landfill were interviewed regarding 11 landfill impacts: direct impacts (odour, litter, dust, noise and similar issues) and indirect impacts (traffic, property values and all off-site impacts). The degree of concern is categorised into 'no problem', 'minor problem', and 'major problem'. Interestingly, indirect impacts generate more serious concerns than direct impacts. The statistical significance of the variation associated with proximity to landfill and roadway location is assessed using two standard non-parametric statistics; the gamma ($\gamma$) statistics and theta (□) statistics (Freeman, 1965). Despite greater concern over indirect impacts, the concerns over in-situ operational impacts are more spatially sensitive along with property devaluation. For example, distance to the landfill explains 59% of the variation in concern over property devaluation. Such results validate the concept of 'spatial externality fields', first developed by the geographer Dean to indicate the extent of negative externalities from undesirable land uses (1977 in Furuseth, 1990, p.270). In hedonic studies, this concept involves specification of landfill variable in a nonlinear or discrete form over different distance ranges.

Hirshfeld et al. (1992) conduct a survey of eight professional real estate appraisers. These real estate appraisers were asked to assess the values of houses when a landfill is located in the neighbourhood. Distance to the landfill is the indicator of the adverse impacts of landfill. Apart from the positive relation between distance and prices, there are several other interesting findings. Firstly, property devaluation occurs at a declining rate as distance increases. Secondly, more valuable houses experience greater depreciation up to a distance of 2 miles. Lastly, the boundary of landfill impact is 3 miles.

Okeke and Armour (2000) conduct a survey similar to that of Furuseth (1990) and draw similar results. The site selected is the Halton landfill in Ontario, Canada, which suffered from community opposition before opening in 1992. The survey is particularly designed to measure perceptions before and during the operation of the landfill. The questionnaire is distributed to households located within 3000 m of the landfill during the summer of 1996 and 76 out of 87 questionnaires are completed. The results of the survey show that among the primary concerns of residents, property devaluation is the major concern, followed by water and air pollution both before and during the operation. The degree of concern is categorised into 'no concerned', 'a little concerned', and 'very concerned'. The results reveal that operational impacts, such as noise, odour and dust from the landfill as well as traffic impacts impose no concerns or only minor concerns to the residents, but environmental and economic impacts are considered more weighty issues, as in Furuseth (1990). This result can be explained by the lack of mitigation measures for groundwater pollution coupled to property-value losses (while the regional authorities have taken measures to address the residents' common concerns about landfill operations). They also find that the degree of concern decreases as distance from the landfill increases.

### 3.3.3 The Implications of the Literature Review

The foregoing literature review reveals that in 34 out of 40 studies there was statistically significant evidence of property devaluation due to proximity to landfill sites albeit of varying magnitude. I now summarise some of the dominant characteristics of the literature and its implications for my empirical analysis.

The geographical area most frequently studied is North America. This literature mostly concerns itself with the impacts from the nearest landfill site. These hedonic analyses of landfill vary greatly in terms of size ranging from 50 to 45,899 observations on house prices. Regarding the study period, most studies used property transactions occurring over 1-5 years but one or two studies used an exceptionally long time period, like Kinnaman (2009) which investigated a property market over 40 years

Second, of 40 hedonic studies reviewed, 23 studies choose to analyse the disamenity impact of a single landfill. In 13 studies the researchers pooled results taken from different communities. The remaining 4 studies are multiple-site cases, in which some households could be simultaneously located within the spatial externality field of more than one landfill site (Blomquist et al., 1988; Ketkar, 1992; Clark and Nieves, 1994; Cambridge Econometrics et al., 2003). These latter studies employ the number of sites or site density as a measure of disamenity impacts rather than distance to the nearest site. Blomquist et al. (1989) and Ketkar (1992) use aggregate data whereas Clark and Nieves (1994) and Cambridge Econometrics et al. (2003) use individual property prices. Whilst Clark and Nieves (1994) use a large micro-level data, the geographic density of landfill sites is not computed for each property but for a wide geographical area, specifically the county in which each property is located. Cambridge Econometrics et al. (2003) utilise by far the largest dataset of any study in terms of the number of properties as well as landfill sites and attempt to solve the problem of houses located with the spatial externality field of many landfill sites by aggregating the geographical area given over to landfill within a given distance from the property (in addition to distance to the nearest site).

Third, a strand of literature identifies a differentiated impact of landfill due to the perception of environmental risk on the part of house owners or buyers. This literature emphasises the importance of taking account of available information or publicity about studied sites and their specific condition. Some studies link risk perception about landfills to landfill life expectancy while there are six studies which explicitly draw a distinction between open and closed sites. Of these studies, only two (Skabursis, 1989 and Kinnaman, 2009) suggest that closed landfill sites may still cause considerable disamenity impacts to nearby residents.

Fourth, distance measures are the most common proxy for landfill disamenity impacts. Numerous studies attempt to identify a critical distance cut-off beyond which impacts disappear altogether. Some studies compare alternative assumptions regarding cut-off distances whereas others simply imposed a cut-off distance, commonly at 2-4 km from landfill. A 2 km zone is also often used in epidemiological studies of health impacts as the likely limit of dispersion for landfill emissions (Elliot et al., 2001). The most popular way to specify decaying effects over distance is through use of concentric zones.

Fifth, results across studies vary depending on the site-specific characteristics of landfills and in particular the amount and type of waste accepted. Frequently authors either estimate separate regressions for sites dealing with particular types of waste or else use dummy variables to identify different waste streams. Ready (2005) found insignificant disamenity impacts from small landfills. On the other hand, statistically significant disamenity effects are found where sites are large or highly contaminated (e.g. Nelson, 1992; Smolen et al., 1992; Arimah, 1996). Some studies estimate more specific disamenity effects such as view, wind direction, distance to the main access road of landfill.

Sixth, only a few studies consider segmented housing markets in a sense that they explore whether landfill disamenity impacts significantly vary across geographically and structurally different submarkets. While Michaels and Smith (1990) use the definition of separate markets provided by real estate agencies, most studies use house prices or a certain housing characteristics to define submarkets.

Seventh, most hedonic house price studies employ linear, semi-log and log-linear functional forms due to their relatively easy interpretation and simple estimation. In some studies, more than one form is used to test whether the results are robust with respect to a change in specification. However, the wider hedonic literature clearly suggests using a flexible functional form based on the Box-Cox transformation which enables us to test what is the most appropriate functional form.

Finally, studies vary considerably in the extent to which other, arguably more important determinants of house prices are included. Many studies employ only a limited set of structural, neighbourhood and environmental housing attributes. Few studies for example include any kind of accessibility variable measuring the distance to various local amenities such as shops or airports.

Having reviewed the literature it is appropriate to explain the way in which our study tries to make a contribution.  The current research extends the literature which investigates long term impacts by comparing open and close sites. It is in this literature common to encounter separate regressions for closed and active landfill sites, or for researchers pooling data across several landfill sites to use a dummy variable to identify those landfill sites that have been closed.

However, much less attention has been paid to the precise duration of long-term impacts after site closure. As in Kinnaman (2009), the existence of post closure impacts may extend over not just years but decades. The current analysis estimates the disamenity impact of a large number of landfill sites some of which closed decades ago.

Likewise it is also important to consider how the geographical limit of disamenity impacts changes as sites close. Seemingly for the first time we consider the possibility that the geographical limit of impacts changes once a site is closed.

This study also contributes on the geographical imbalance of previous studies which mainly from the US.

In addition, a detailed set of controls may better enable us to identify the disamenity effect of landfills compared to previous studies most of which include only a limited number of structural-type and accessibility-type variables.

Most importantly, this study investigates, using microeconomic data, the impact of landfill sites on property values in the context of a situation where properties are simultaneously located close to more than one landfill site. I believe this to be the norm at least for large metropolitan areas. While there are studies which take into account the presence of multiple sites near residential properties, most of them use aggregate data which produce inferior results when compared to those using microeconomic data. And none of them include any historical sites either.

For other additional factors of house prices, spatial dependence has widely been explored in hedonic property value studies. Ignoring spatial autocorrelation among houses in terms of prices or characteristics may lead us to the problem of omitted variables or lack of efficiency. Spatial models are able to control for the type or value of property in the surrounding area, which is highly likely to influence house price. Thus the current study further explores a systematic specification of such effects with various spatial models. The implication drawn for the current study will be discussed further in detail in the section of model specification.

## 3.4 Data

The geographical focus of this hedonic study of landfill disamenities is the City of Birmingham in the UK. Birmingham is a metropolitan borough in the West Midlands of England with a total area of 267.77 $km^2$. It is the second most populous city in the UK with a population of 1,036,900 in 2010 (993,700 in 1997). Annual earning for full-time employee jobs is the same with the national average £500.3 in 2010 (£327.4 in 1997, slightly higher than the national average). Unemployment rate is 12.8 % in 2011, much higher than the national rate 7.7% (11.4% in 1997 with national rate 7%). Notably Birmingham is the most ethnically diverse cities in the UK with growing population of ethnic minority.

This study utilises a comprehensive set of data collected for the purposes of a hedonic study of noise pollution (Bateman et al., 2004) and includes the selling prices of a large number of properties along with their structural, accessibility, neighbourhood and environmental characteristics. This dataset is further enriched by the addition of data on the geographical location of landfill sites as well as by a range of other neighbourhood variables.

### 3.4.1 The City of Birmingham Dataset

#### 3.4.1.1 Property Prices and Locations

Bateman et al. (2004) obtain records of all property sales within the administrative boundaries of the City of Birmingham during 1997 from the UK Land Registry. The data taken from the Land Registry includes the full market price of property, date of sales and full property address. The dataset includes only residential property transactions and ignores first-time right-to-buys since they may not reflect the full market price.

### 3.4.1.2 Structural Characteristics

Most of structural characteristics of property included in the dataset are obtained from Valuation Office Agency (VOA) property characteristics data. The VOA bands the value of properties for council tax purposes. In undertaking the valuations, the VOA needs to take account of the characteristics of residential property and everything that goes to make up its value. The structural variables included in the hedonic regressions are presented in Table 3.2.

**Table 3.2: Structural characteristics**

| Variable name | Definition | Research hypothesis |
|---|---|---|
| Floor Area | The floor area of each property. For flats this is the internal area. For all other properties it is the external area ($m^2$) | Properties with larger floor area will be more valuable such that a positive coefficient is anticipated. |
| Age | Each property is coded into one of 7 age bands with properties built after 1973 coded with the actual year of construction | The relationship is not entirely clear. Some buyers prefer older houses because of their unique characteristics while other buyers may prefer more modern properties. |
| Bedrooms | The number of bedrooms at each property | Properties with more bedrooms will be more valuable such that a positive coefficient is anticipated. |
| WCs | The number of internal WC's at each property | Properties with more WCs will be more valuable such that a positive coefficient is anticipated. |
| Floors | The number of floors in house | Properties with more storeys will be more valuable than those with fewer storeys such that a positive coefficient is anticipated. |
| Garage | One if the property has a garage and zero otherwise. | Properties with a garage will be more valuable such that a positive coefficient is anticipated. |

**Figure 3.4: Location of properties within the City of Birmingham**

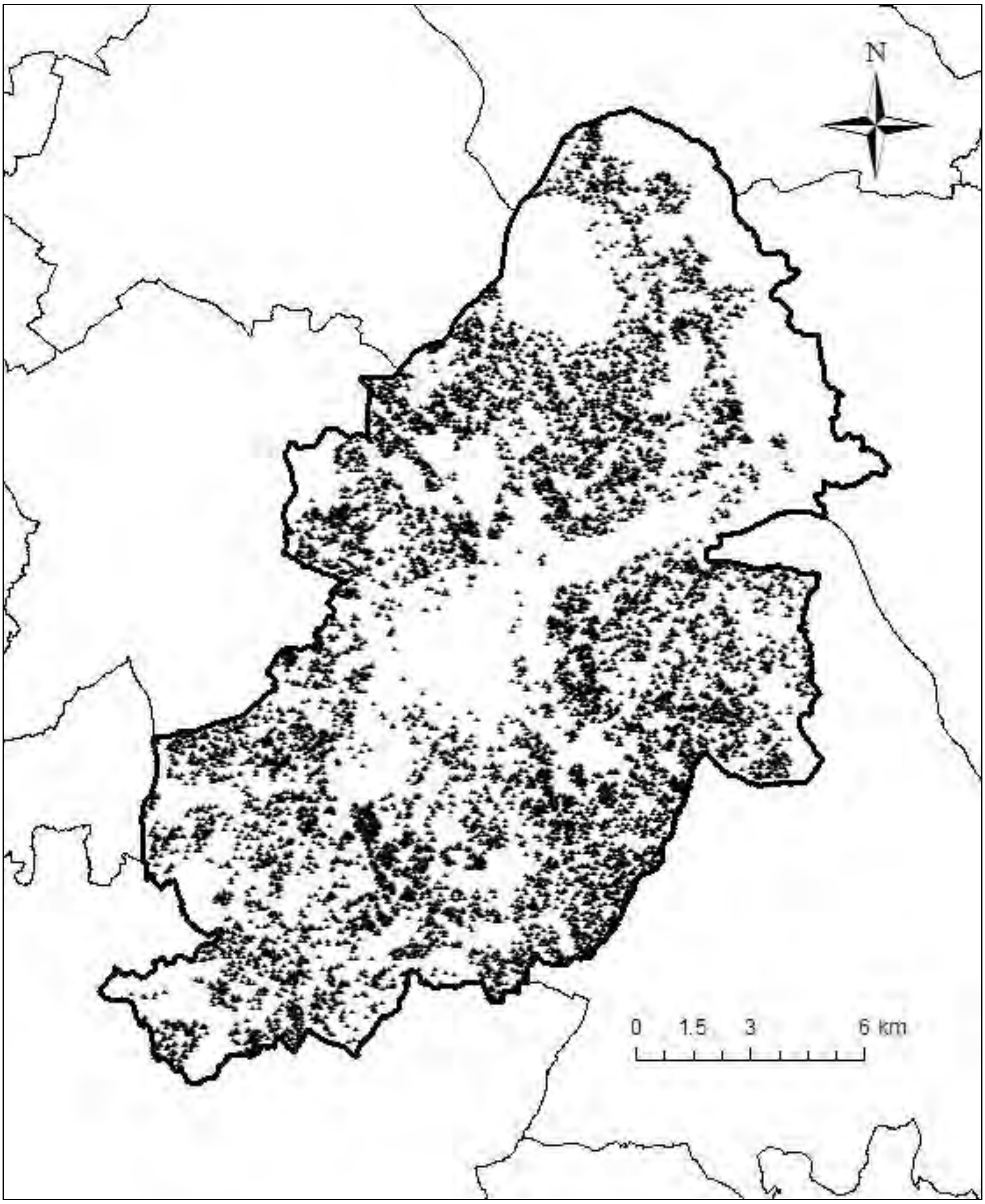

**Table 3.3: Construction types and beacon group**

| Variable name | Definition | Research hypothesis |
|---|---|---|
| **Construction types**<br>Detached Bungalow<br>Semi-Detached Bungalow<br>End Terrace Bungalow<br>Terrace Bungalow<br>Detached House<br>Semi-Detached House<br>End Terrace House<br>Terrace House | Dummy variable for each type. Semi-detached house is taken as the baseline property type. | The coefficients on each property type dummy variable reflect the relative difference in price between that property type and a Semi-detached house. |
| **Beacon Group**<br>BG 1(Unrenovated cottage pre 1919)<br>BG 2(Renovated cottage pre 1919)<br>BG 3 (Small "industrial" pre 1919)<br>BG4 (Medium "industrial" pre 1919)<br>BG 5 (Large terrace pre 1919)<br>BG 8 (Small "villa" pre 1919)<br>BG 9 (Large "villas" pre 1919)<br>BG 10 (Large detached pre 1919)<br>BG 19 (Houses 1908 to 1930)<br>BG 20 (Subsidy houses 1920s & 30s)<br>BG 21 (Standard houses 1919-45)<br>BG 24 (Large houses 1919-45)<br>BG 25 (Individual houses 1919-45)<br>BG 30 (Standard houses 1945-53)<br>BG 31 (Standard houses post 1953)<br>BG 32 (Large houses post 1953)<br>BG 35 (Individual houses post 1945)<br>BG 36 ( "Town Houses" post 1950) | Dummy variable for each beacon group. Beacon group is defined by the VOA and is used to identify similar properties in terms of style and age. BG21 (Standard houses 1919-45) is taken as the baseline property type. | The coefficients on each beacon group dummy variable reflect the relative difference in price between properties of that beacon group and a property of BG 21. |

The construction type of the property and the 'beacon groups' are also included as structural variables. Beacon groups are typical property types defined by the VOA based on the age, size, architectural type and quality of a property. There are 8 types of construction and 18 beacon groups identified in the property market of Birmingham in 1997. Table 3.3 describes each type of construction and beacon group.

In addition, the garden area ($m^2$) is calculated for each property by matching the grid references with the building outlines on OS Land-Line.Plus (Ordnance Survey, 1996). Land-

Line.Plus digital map data provide land parcel boundaries, road kerbs, rivers and water features. Such geographical information is used to calculate the land uses visible from each property and the proximity of the property to nearby roads. These characteristics are further described in accessibility and environmental characteristics (see below).

#### 3.4.1.3 Neighbourhood Characteristics

Neighbourhood characteristics describe the socio-demographic, economic characteristics and ethnic composition of the local area in which the property is located. Data are taken from the 1991 census conducted by the Office for National Statistics (ONS) at enumeration district (ED) level (this is the smallest census area available).

**Table 3.4: Neighbourhood characteristics**

<table>
<tr><th>Variable name</th><th>Definition</th><th>Research hypothesis</th></tr>
<tr><td>Unemployment</td><td>Unemployment proportion</td><td>Properties in neighbourhoods with a higher unemployment rate will be priced lower such that a negative coefficient is anticipated.</td></tr>
<tr><td>Family with children</td><td>Proportion of households with children</td><td>Properties in neighbourhoods with more families tend to show higher prices in the market such that a positive coefficient is anticipated.</td></tr>
<tr><td>Age60</td><td>Proportion of residents over the age of 60</td><td>Though the relationship is not entirely clear, properties with more fraction of population age 60 and older in neighbourhoods will show higher prices in the market such that a positive coefficient is anticipated.</td></tr>
<tr><td>White</td><td>Proportion of non-white residents</td><td rowspan="3">The increasing presence of members of the ethnic minorities in neighbourhoods can impact upon house prices</td></tr>
<tr><td>Black</td><td>Proportion of black (African or Caribbean) residents</td></tr>
<tr><td>Asian</td><td>Proportion of Asian residents</td></tr>
</table>

In our dataset 1,743 EDs are identified in Birmingham. The variables (unemployment, family composition, age composition and ethnically-concentrated neighbourhoods) are chosen on the basis of previous literature. Table 3.4 provides a description of these neighbourhood attributes. These variables represent aggregate-level data of on average 174 households in each ED. In addition to neighbourhood variables, dummies for the 39 electoral wards in Birmingham are used as political boundaries, as displayed in Figure 3.5 and summarised in Table 3.5.

**Figure 3.5: Wards in the City of Birmingham**

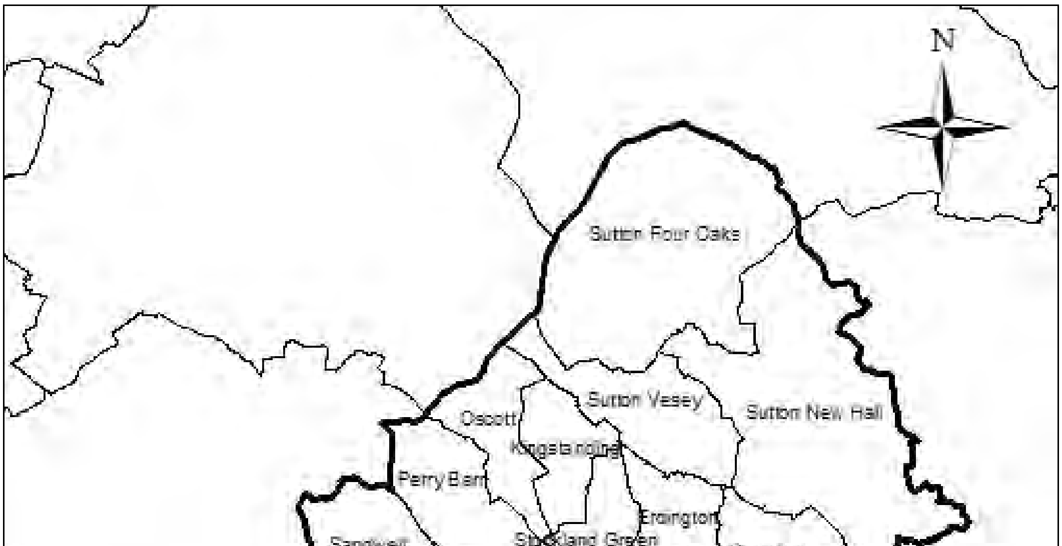

**Table 3.5: Dummies of wards in the City of Birmingham**

| Variable name | | Research Hypothesis |
|---|---|---|
| 39 Ward level dummy variables | Acock's Green<br>⋮<br>Yardley | These 38 dummy variables provide a reasonably fine spatial categorisation of properties by geographical location. The baseline ward is Acock's Green. Thus, the coefficients on each ward dummy variable reflect the relative difference in price between properties located in that ward and a property in Acock's Green. |

### 3.4.1.4 Accessibility Characteristics

Accessibility variables measure residential proximity to various local amenities or disamenities. Distance to the nearest amenity or disamenity is obtained using GIS and measured in terms of walking time in minutes, car travel time in minutes and straight-line distance in kilometres. Table 3.6 describes the accessibility variables used in this study and provides the data source for each amenity or disamenity. When considering accessibility to primary schools and shops, the quality of schools and the number of shops is further taken into account using the following formula:

$$A_i = \sum_{j=1}^{J} \alpha_j e^{-\delta d_{ij}} \qquad \textbf{(3.7)}$$

where $A_i$ is accessibility at property $i$, $\alpha_j$ is the attractiveness of shop $j$, $d_{ij}$ is the walking distance in kilometres between property $i$ and shop $j$, $\delta$ is an exponent for distance decay and J is the number of shops in the region. Bateman et al. (2004) set $\delta = 2$ (such that a shop located at 100m away from the property receives a weight over 6 times that of a shop at 1 km distance; and shops at over 2 km distance receive almost no weight at all) and $\alpha_j = \alpha = 1$ (such that all shops are considered equally attractive).

**Table 3.6: Accessibility characteristics**

| Variable name | Definition | Research Hypothesis |
|---|---|---|
| Railway Station | Walk time to the nearest railway station(mins) | Property prices will be higher near to transport links such that a negative coefficient is anticipated. |
| Park | Walk time to the nearest park(mins) | Property prices will be higher near to recreational sites like park, such that a negative coefficient on walking time is anticipated. |
| University | Walk time to University/ Queen Elizabeth Hospital (mins) | Though the relationship is uncertain, proximity to schools and hospitals is commonly expected to contribute positively to property prices. |
| CBD | Drive time to Central Business centre (mins) | Property prices will be higher near to CBD such that a negative coefficient is anticipated. |
| Motorway Junction | Drive time to the nearest motorway junction (mins) | Property prices will be higher near to motorway junctions as accessibility by car increases (given we have controlled for noise and air pollution). The coefficient will be negatively signed. |
| Airport | Drive time to Birmingham Airport (mins) | Property prices will be higher near to airport as employment opportunities offered by the airport and transport accessibility increase (given we have controlled for noise pollution). The coefficient will be negatively signed. |
| Mosque | Straight line distance to the nearest mosque (km) | The relationship is not certain. |
| Industry A | Straight line distance to the nearest EA-regulated Part A large industry (km) | Property prices will be lower near to both types of industrial sites though Industry A has a larger impact. The coefficients will be negatively signed. |
| Industry B | Straight line distance to the nearest local authority-regulated Part B large industry (km) | |
| Motorway | Straight line distance to the nearest motorway (km) | Property prices will be higher near to road network as roads permit easy access to local amenities (given we have controlled for noise and air pollution). The coefficient will be negatively signed. |
| A Road | Straight line distance to the nearest A road (km) | |
| B Road | Straight line distance to the nearest B road (km) | |
| Minor Road | Straight line distance to the nearest minor road (km) | |
| Railway Line | Straight line distance to the nearest railway line (km) | Property prices will be lower near to railway line. |
| Primary Schools | Weighted average of inverse walking distance with performance of nearby primary schools | High scores of the variable for primary school indicate increasing quality and/or ease of access. Property prices will be higher near to better primary schools such that a positive coefficient is anticipated. |

| | | |
|---|---|---|
| Shops | Weighted average of inverse walking distance with number of local shops | Property prices will be higher near to bigger local centre. |

Accessibility to primary schools is computed using the same procedure. For each primary school in the Birmingham area, an estimate of school quality is calculated as the percentage of pupils achieving Level 4 or above in Science, Mathematics and English (the level expected of 11 year olds). A primary school accessibility index is constructed with the weight $\alpha_j$ set to this measure of school quality and $\delta$ = 1. Table 3.6 describes the accessibility variables employed. See Appendix 3.1 for the data source for each variable. The coefficients on accessibility variables will be negative if sites are an amenity and positive if a disamenity.

#### 3.4.1.5 Environmental Characteristics

Three types of environmental characteristics are computed using data extracted from various sources: visual impacts of a variety of land uses, noise level and air pollution. For visual quality of an area experienced by residents, four land uses are chosen: water, parks, roads and railway. Table 3.7 illustrates descriptions of environmental characteristics.

**Table 3.7: Environmental characteristics**

| **Variable** | **Definition** |
|---|---|
| Water Views | View of water features ($m^2$) |
| Park Views | View of park ($m^2$) |
| Road Views | View of road ($m^2$) |
| Rail Views | View of rail ($m^2$) |
| Road Noise | Noise from road maximum(dB) |
| Rail Noise | Noise from rail maximum(dB) |
| Airport Noise Night | Noise from aircraft at night(dB) |
| Airport Noise Day | Noise from aircraft at day(dB) |
| $NO_2$ | Levels of $NO_2$ pollution |
| CO | Levels of CO pollution |

The view of each land uses from property can be calculated by taking account of the height of land which each property is built on as well as the location and heights of buildings which can be seen from property. Land height contours are extracted from Land-Form PROFILE (Ordnance Survey, 1996). This is combined with the outlines of all buildings from Land-Line.Plus (Ordnance Survey, 1996) and furthermore each building is assumed to be 9 m high. Given that a 1 $m^2$ grid represents its height, the area of land visible from each property is computed using GIS.

Noise data for each property is obtained from the Birmingham 1 projects (DETR, 2000) which produced gridded noise contour maps for road and rail noise in Birmingham. The noise level data are supplied for each residential address in Birmingham. Using ADRESS-POINT, the data are grid referenced and matched with the property sample. Due to lack of data on noise level for some properties, the sample is reduced to 10,792 property transactions.

Air quality across areas in Birmingham is assessed by Birmingham City Council (WMCOJPG, 2000). The concentrations of nitrogen dioxide ($NO_2$) and carbon monoxide (CO) are computed for every grid cell size of 250 m, based on 1998 traffic flows and emissions within the City of Birmingham. Using GIS, the emission level of both pollutants are estimated for each property

Table 3.8 shows the descriptive statistics of the variables in the dataset. The average price of houses is £58,996 in 1997. Floor area varies from 42 $m^2$ to 645 $m^2$. The oldest house is 100 years old and the number of bedrooms varies from 1 to 12 with an average of 3 beds. Property transactions occurred with similar frequencies across all quarters of the year. More than 70% of houses are semi-detached or terrace houses while about 50% are BG4 (medium "industrial" pre 1919) or BG21 (standard houses 1919-45). The dataset also includes 38 dummy variables of wards for unobserved submarket heterogeneity across different political boundaries. These pre-defined submarkets, however, may not be a correct form of market segmentation. Among neighbourhood characteristics, whites account for more than 80% of the population in an average ED. The mean number of blacks and Asian are merely 5% and 13% respectively but Asians account for more than 90% of the population in some EDs.

Among the environmental variables, the mean level of noise varied from 30-50 dB. However, the noise level from rail, road and airport ranged around 65-75 dB at the maximum. According to the World Health Organisation (WHO), guideline values for community noise are 30-45 dB for residential areas. To protect people from being seriously (moderately) annoyed from community noise during the daytime, the noise level should not exceed 55 dB (50 dB). During the evening and night the noise level should be 5-10 dB lower than during the day (Berglund and Lindvall, 1995). Therefore, in estimating the hedonic regression, I invoke the conventional threshold of 55 dB, as it is the maximum level of tolerable noise as in Bateman et al. (2004).

**Table 3.8: Descriptive statistics**

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| ***Dependent variable*** | | | | |
| Price(£) | 58,996.09 | 36,253.55 | 9,500 | 645,003 |
| ***Structural characteristics*** | | | | |
| Floor Area ($m^2$) | 102.586 | 32.707 | 42 | 645 |
| Garden Area ($m^2$) | 225.97 | 208.454 | 0 | 5,164.21 |
| Age (decades) | 6.481 | 2.66 | 0 | 10 |
| Bedrooms | 2.961 | 0.669 | 1 | 12 |
| WCs | 1.216 | 0.438 | 1 | 5 |
| Floors | 2.007 | 0.248 | 1 | 7 |
| Garage (proportion) | 0.435 | 0.496 | 0 | 1 |
| Sales date (proportion) | | | | |
| 1st Quarter (Jan. to Mar.) | 0.213 | 0.409 | 0 | 1 |
| 2nd Quarter (Apr. to June) | 0.245 | 0.43 | 0 | 1 |
| 3rd Quarter (July to Sept.) | 0.287 | 0.453 | 0 | 1 |
| 4th Quarter (Oct. to Dec.) | 0.254 | 0.435 | 0 | 1 |
| Construction Type (proportion) | | | | |
| Detached Bungalow (10) | 0.013 | 0.111 | 0 | 1 |
| Semi-Detached Bungalow (11) | 0.008 | 0.09 | 0 | 1 |
| End Terrace Bungalow (12) | 0.0004 | 0.022 | 0 | 1 |

| | | | | |
|---|---|---|---|---|
| Terrace Bungalow (13) | 0.0002 | 0.017 | 0 | 1 |
| Detached House (20) | 0.115 | 0.319 | 0 | 1 |
| Semi-Detached House (21) | 0.396 | 0.489 | 0 | 1 |
| End Terrace House (22) | 0.115 | 0.319 | 0 | 1 |
| Terrace House (23) | 0.353 | 0.478 | 0 | 1 |
| Beacon Group (proportion) | | | | |
| 1.Unrenovated cottage pre 1919 | 0.0003 | 0.019 | 0 | 1 |
| 2. Renovated cottage pre 1919 | 0.001 | 0.027 | 0 | 1 |
| 3. Small “industrial” pre 1919 | 0.04 | 0.195 | 0 | 1 |
| 4.Medium “industrial” pre 1919 | 0.226 | 0.418 | 0 | 1 |
| 5. Large terrace pre 1919 | 0.006 | 0.078 | 0 | 1 |
| 8. Small “villa” pre 1919 | 0.02 | 0.138 | 0 | 1 |
| 9. Large “villas” pre 1919 | 0.009 | 0.093 | 0 | 1 |
| 10. Large detached pre 1919 | 0.003 | 0.058 | 0 | 1 |
| 19. Houses 1908 to 1930 | 0.011 | 0.103 | 0 | 1 |
| 20. Subsidy houses 1920s & 30s | 0.14 | 0.347 | 0 | 1 |
| 21. Standard houses 1919-45 | 0.257 | 0.437 | 0 | 1 |
| 24. Large houses 1919-45 | 0.016 | 0.124 | 0 | 1 |
| 25. Individual houses 1919-45 | 0.0004 | 0.022 | 0 | 1 |
| 30. Standard houses 1945-53 | 0.045 | 0.207 | 0 | 1 |
| 31. Standard houses post 1953 | 0.19 | 0.392 | 0 | 1 |
| 32. Large houses post 1953 | 0.032 | 0.177 | 0 | 1 |
| 35. Individual houses post 1945 | 0.001 | 0.036 | 0 | 1 |
| 36. “Town Houses” post 1950 | 0.004 | 0.062 | 0 | 1 |
| ***Wards (proportion)*** | | | | |
| Acock's Green | 0.039 | 0.194 | 0 | 1 |
| Aston | 0.015 | 0.123 | 0 | 1 |
| Bartley Green | 0.018 | 0.131 | 0 | 1 |
| Billesley | 0.027 | 0.162 | 0 | 1 |
| Bournville | 0.038 | 0.191 | 0 | 1 |
| Brandwood | 0.022 | 0.147 | 0 | 1 |
| Edgbaston | 0.02 | 0.14 | 0 | 1 |
| Erdington | 0.029 | 0.168 | 0 | 1 |
| Fox Hollies | 0.028 | 0.165 | 0 | 1 |
| Hall Green | 0.041 | 0.198 | 0 | 1 |
| Handsworth | 0.016 | 0.125 | 0 | 1 |
| Harborne | 0.036 | 0.186 | 0 | 1 |
| Hodge Hill | 0.024 | 0.154 | 0 | 1 |
| King's Norton | 0.016 | 0.125 | 0 | 1 |
| Kingsbury | 0.01 | 0.101 | 0 | 1 |
| Kingstanding | 0.022 | 0.146 | 0 | 1 |
| Ladywood | 0.014 | 0.118 | 0 | 1 |
| Longbridge | 0.023 | 0.15 | 0 | 1 |
| Moseley | 0.024 | 0.152 | 0 | 1 |
| Nechells | 0.019 | 0.137 | 0 | 1 |
| Northfield | 0.028 | 0.164 | 0 | 1 |

| | | | | |
|---|---|---|---|---|
| Oscott | 0.026 | 0.158 | 0 | 1 |
| Perry Barr | 0.033 | 0.18 | 0 | 1 |
| Quinton | 0.024 | 0.152 | 0 | 1 |
| Sandwell | 0.028 | 0.164 | 0 | 1 |
| Selly Oak | 0.044 | 0.205 | 0 | 1 |
| Shard End | 0.02 | 0.138 | 0 | 1 |
| Sheldon | 0.021 | 0.144 | 0 | 1 |
| Small Heath | 0.028 | 0.164 | 0 | 1 |
| Soho | 0.018 | 0.135 | 0 | 1 |
| Sparkbrook | 0.013 | 0.111 | 0 | 1 |
| Sparkhill | 0.021 | 0.142 | 0 | 1 |
| Stockland Green | 0.028 | 0.166 | 0 | 1 |
| Sutton Four Oaks | 0.038 | 0.190 | 0 | 1 |
| Sutton New Hall | 0.044 | 0.206 | 0 | 1 |
| Sutton Vesey | 0.039 | 0.194 | 0 | 1 |
| Washwood Heath | 0.028 | 0.164 | 0 | 1 |
| Weoley | 0.017 | 0.13 | 0 | 1 |
| Yardley | 0.024 | 0.153 | 0 | 1 |
| ***Neighbourhood characteristics (%)*** | | | | |
| Age60 | 20.86 | 7.79 | 2.97 | 64.2 |
| Unemployment | 11.79 | 8.55 | 1.03 | 50 |
| White | 82.34 | 23.141 | 4.95 | 100 |
| Black | 4.30 | 0.056 | 0 | 42.83 |
| Asian | 13.36 | 0.2 | 0 | 90.67 |
| Family with children | 31.46 | 10.16 | 2.94 | 84.27 |
| ***Accessibility characteristics*** | | | | |
| Primary schools | 0.602 | 0.177 | 0.15 | 0.97 |
| Shops | 2.279 | 1.275 | 0.07 | 9.56 |
| Rail Station (mins) | 30.763 | 16.881 | 0.351 | 92.081 |
| Park (mins) | 15.009 | 9.298 | 0.053 | 57.078 |
| University (mins) | 137.13 | 73.228 | 0.917 | 339.293 |
| CBD(mins) | 21.872 | 7.972 | 3.467 | 53.118 |
| Motorway Junction (mins) | 16.228 | 6.3 | 0.171 | 38.92 |
| Airport (mins) | 39.799 | 10.913 | 10.037 | 73.098 |
| Mosque (km) | 2.686 | 1.765 | 0.00001 | 9.036 |
| Industry A (km) | 2.462 | 1.82 | 0.022 | 10.204 |
| Industry B (km) | 0.814 | 0.528 | 0.010 | 3.333 |
| Motorway(km) | 3.761 | 2.074 | 0.030 | 8.370 |
| Road A (km) | 0.529 | 0.442 | 0.006 | 2.459 |
| Road B (km) | 0.659 | 0.522 | 0.005 | 3.401 |
| Minor Road (km) | 0.016 | 0.02 | 0.002 | 0.639 |
| Railway (km) | 0.809 | 0.556 | 0.006 | 2.778 |
| ***Environmental characteristics*** | | | | |
| Water View ($m^2$) | 0.479 | 7.541 | 0 | 348.63 |
| Park View ($m^2$) | 6.289 | 36.83 | 0 | 664.03 |

| | | | | |
|---|---|---|---|---|
| Road View ($m^2$) | 18.05 | 9.7 | 0 | 101.54 |
| Rail View ($m^2$) | 0.584 | 3.89 | 0 | 196.95 |
| Road Noise (dB) | 49.84 | 9.444 | 31.6 | 75.8 |
| Rail Noise(dB) | 36.81 | 12.557 | 0 | 74.7 |
| Airport Noise Night (dB) | 2.058 | 10.211 | 0 | 64.42 |
| Airport Noise Day (dB) | 4.764 | 16.045 | 0 | 69 |
| $NO_2$ | 89.593 | 26.655 | 50.4 | 410.84 |
| CO | 2.174 | 0.92 | 0.48 | 5.51 |

We expect some correlation between independent variables, in particular neighbourhood characteristics, accessibility characteristics, environmental characteristics. As expected, distance to amenity or disamenity places which involve transportation infrastructure are positively correlated with the level of air pollutants. Noise levels are moderately related to the distance to each source, such as airport, road and rail.

### 3.4.2 Landfill Data Analysis

Data on landfill sites in West Midlands are obtained from the EA and Envirocheck Report (2006).[55] Both data sources provide geographic location data, dates of first and last waste accepted, type of waste buried and waste control measures taken. However, Envirocheck Report provides only data on active sites with their specific site characteristics (which are often not available in EA data).

Figure 3.6 shows these landfill sites which are located within 5 km of houses sold in 1997. The total number of landfill sites within the border of Birmingham is 53 which consisting of 51 historical and 2 active sites in 1997.[56] Of active landfills, the site in the centre of

[55] Landmark Information Group Limited produced the report jointly with several other data providers, including (but not limited to) Ordnance Survey, British Geological Survey, the Environment Agency and English Nature.The report contains information on environmental sites which are potentially the source of contamination.

[56] Under the Landfill Directive, landfill sites that closed after 16 July 2001 are subject to the requirements of the Directive, such that operators must provide closure plans to show how they intend to close and manage the site after closure. Regarding landfill sites that closed before 16 July 2001, some sites are regulated through environmental permits and subject of the Closed Landfill Review. Although the current study is conducted using house sales in 1997, the results would not change even with the use of data after the Directive effective. This is

Birmingham only accepted industrial waste and operated between 1990 and 2006. The other site within the border of the City is still active. This site is part of the Minworth Sewage Treatment Works operated by Severn Trent. The site is used only for disposal of wastes generated on-site by sewage treatment process, and does not receive any wastes from off-site sources.

However, a somewhat greater number of landfill sites operated in areas just outside the city boundaries of Birmingham. In total, 280 historical sites and 16 active sites are identified within 5 km of houses sold in 1997. As can be seen in Figure 3.6, most of historical landfill sites as well as active sites are located outside the city.

From the map, we can also observe that landfill sites are geographically clustered rather than randomly distributed. One way to analyse spatial patterns of geographical point data is to use Ripley's *K*-function (Ripley, 1977). The deviation of *K*-function from a completely random point process may suggest spatial clustering or dispersion. Appendix 3.2 estimates the *K*-function for active and historical sites using various distance scales accompanied by an interpretation of findings. In short, the results confirm the visual impression that historical sites and active sites are not spatially independent but are instead clustered together. Possibly this is because it is easier to build a landfill site in an area that has already been blighted by the construction of an earlier landfill site.

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because the Directive does not change regulatory approach to historical closed landfills and most of closed sites in birmingham are historical closed sites (no sites are subject to Closed Landfill Review)

**Figure 3.6: Landfill sites within 5 km from houses in Birmingham sold in 1997**

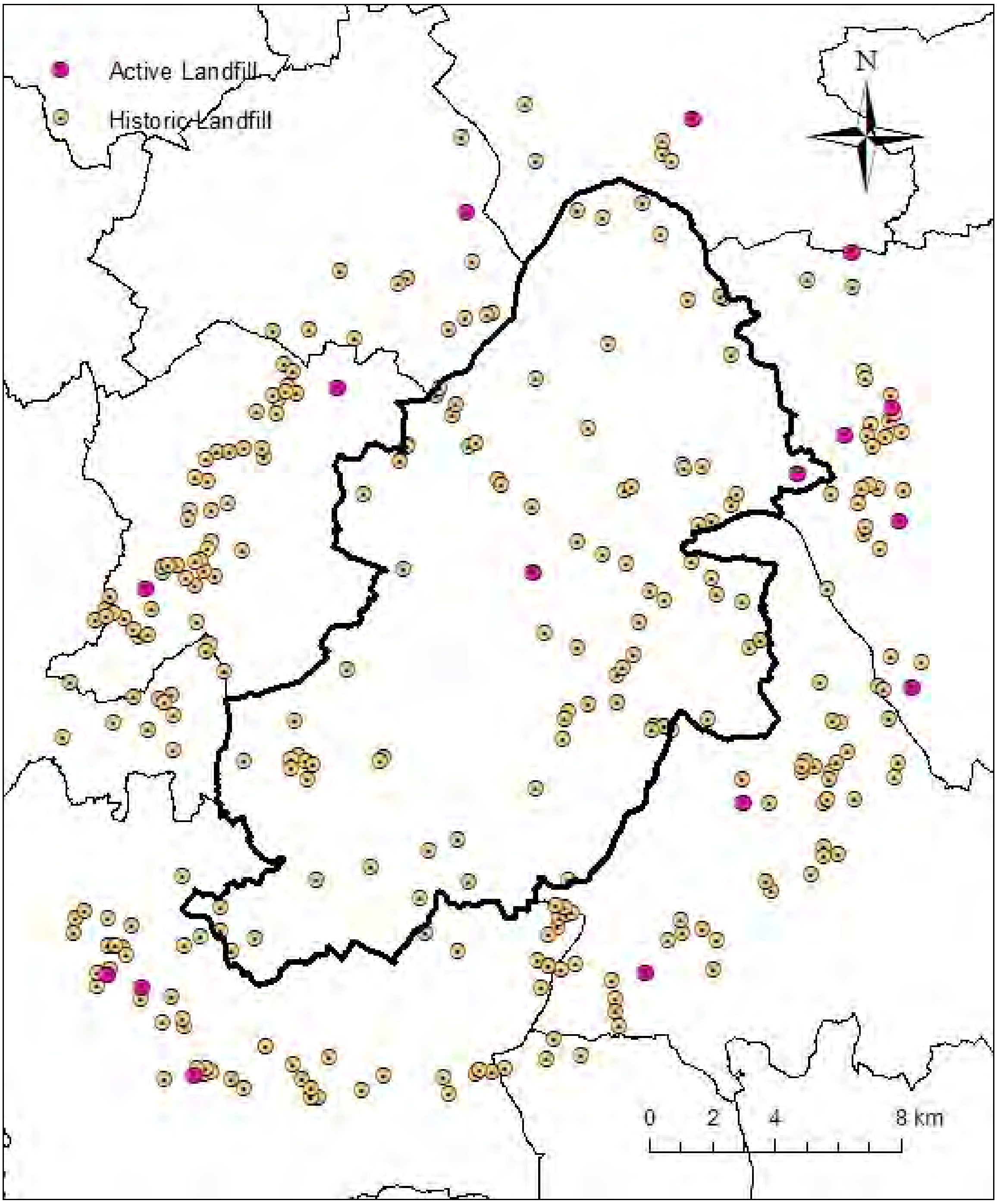



Table 3.9 summarises the descriptive statistics of landfill sites' locations relative to the locations of properties. The average distance to the nearest historical site is around 1 km. However, the average distance is nearly 5 km when only active sites are considered. Table 3.9 also contains information on the relative position of houses to the nearest landfill site

according to the prevailing wind direction which affects the dispersion of air pollutants and windblown material. The assumption is that properties directly downwind from the landfill will be more adversely affected. On average the prevailing wind direction is south-westerly in Birmingham over the period, 1990-1999 (Met Office).[57] Given this, the deviation of the house-site angle from the southwest is calculated and as this measure diminishes properties may experience greater exposure to environmental disamenities.

**Table 3.9: Summary statistics of landfill locations**

| | **Mean** | **Std. Dev.** | **Min** | **Max** |
|---|---|---|---|---|
| Distance to the nearest site (km) | 0.986 | 0.514 | 0.016 | 3.243 |
| Deviation from the prevailing downwind direction (in absolute degrees) | 89.346 | 51.735 | 0.004 | 179.998 |
| Distance to the nearest active site (km) | 4.985 | 1.711 | 0.288 | 9.186 |
| Deviation from the prevailing downwind direction (in absolute degrees) | 90.027 | 48.435 | 0.018 | 179.995 |

Table 3.10 shows the frequency distribution of the distance to the nearest site from residential properties. Most of the nearest sites are situated within 2 km and only a few of these nearest sites are operational in 1997.

**Table 3.10: Frequency distribution of the distance to the nearest site**

| **Distance** | **Frequency** | **Percent** | **Active Frequency** | **Active Percent** |
|---|---|---|---|---|
| ≤ 1 km | 5,999 | 55.59 | 20 | 0.33 |
| 1 km< distance ≤2 km | 4,402 | 40.79 | 72 | 1.64 |
| 2 km< distance ≤3 km | 373 | 3.46 | 2 | 0.54 |
| 3 km< distance ≤4 km | 18 | 0.17 | 0 | 0 |
| Total | 10,792 | 100.00 | 94 | 0.87 |

[57] The Met Office gathers data on wind roses for Birmingham airport (Elmdon). The trend in wind direction through the year was south westerly between January, 1990 and December, 1999. See the Appendix 3.6 for wind direction distribution (%).

**Table 3.11: Frequency distribution of the distance to the nearest active sites**

| Nearest active landfill | Frequency | Percent | Cumulative percent |
|---|---|---|---|
| ≤ 1 km | 20 | 0.19 | 0.19 |
| 1 km< distance ≤2 km | 301 | 2.79 | 2.97 |
| 2 km< distance ≤3 km | 973 | 9.02 | 11.99 |
| 3 km< distance ≤4 km | 1,839 | 17.04 | 29.03 |
| 4 km< distance ≤5 km | 2,828 | 26.20 | 55.24 |
| 5 km< distance ≤6 km | 1,958 | 18.14 | 73.38 |
| 6 km< distance ≤7 km | 1,207 | 11.18 | 84.56 |
| 7 km< distance ≤8 km | 1,071 | 9.92 | 94.49 |
| 8 km< distance ≤9 km | 572 | 5.30 | 99.79 |
| 9 km< distance ≤10 km | 23 | 0.21 | 100.00 |
| Total | 10,792 | 100.00 | 100.00 |

Table 3.11 indicates that most of the nearest active sites are located more than 3 km from properties. Only 12% of properties have an active site within 3 km. Table 12 summarises the number of historicl sites within each concentric zone.

**Table 3.12: Number of historical sites**

| Number of historical sites | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| ≤ 1 km | 0.981 | 1.149 | 0 | 6 |
| ≤ 2 km | 4.004 | 2.582 | 0 | 12 |
| ≤ 3 km | 8.634 | 3.854 | 0 | 20 |
| ≤ 4 km | 14.969 | 4.911 | 2 | 29 |
| ≤ 5 km | 23.582 | 6.411 | 7 | 44 |

Figures 3.7, 3.8 and 3.9 display how many historical sites were present within 1 km, 3 km and 5 km respectively, from each property. In Figure 3.7, about 30% of houses have at least one historical landfill site within 1 km and 15% have two historical sites within 1 km. Figure 3.8 indicates that less than 1% have no or only one historical site within 3 km. According to Figure 3.9, residential properties have at least seven historical sites within 5 km. Evidently many properties lie within the spatial externality field of more than one landfill site (mostly these are historical sites) and any hedonic analysis will need to account for this fact.

**Figure 3.7: Histogram for the number of historical landfills located within1 km**

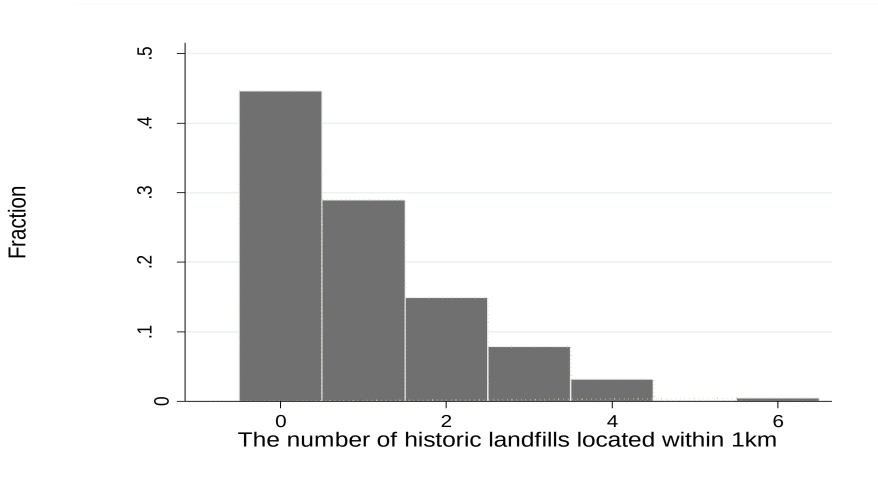



**Figure 3.8: Histogram for the number of historical landfills located within 3 km**

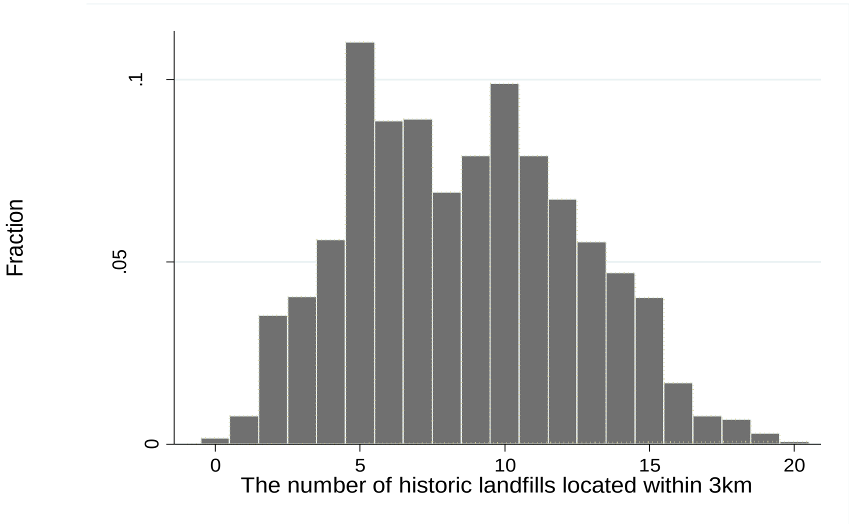



**Figure 3.9: Histogram for the number of historical landfills located within 5 km**

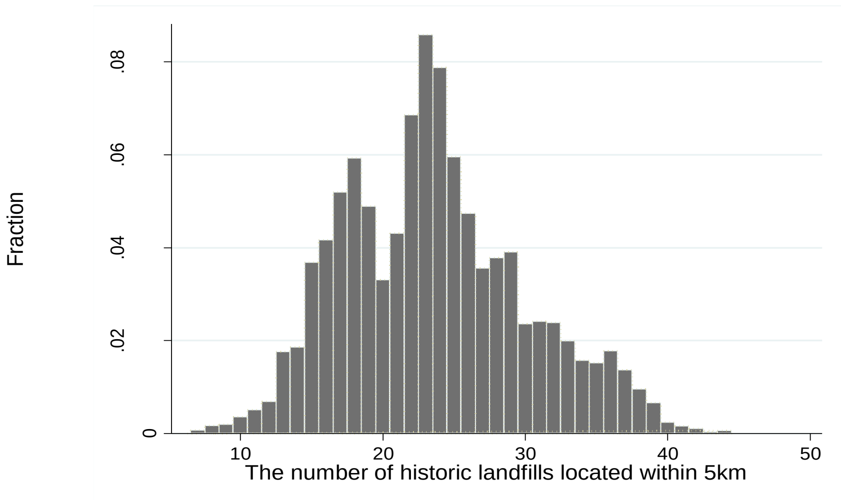


Table 3.13 provides information on types of waste accepted by historical landfills within 5 km from each property. Waste types are categorised into inert, industrial, commercial, household, special and liquids/sludge.[58] Mixed types of waste are buried in 51.78% of the sites while 26.43% of the landfills accept only one specified type of waste. Among single-waste type landfills, the majority are either inert or industrial waste. Compared to landfills specialising in a single type waste, landfills with a mixed composition are associated with greater environmental damages and disamenity impacts. The Landfill Directive which came into force in July 2002 focuses on ensuring that different materials, particularly hazardous materials are segregated from other non-hazardous materials and pre-treated before being buried in landfills.

**Table 3.13: Waste types buried in historical sites**

| Waste type | 100% specified waste type | Co-disposal | No waste of specified type or no data | Total |
|---|---|---|---|---|
| Inert | 48 | 96 | 136 | 280 |
| Industrial | 19 | 124 | 137 | 280 |
| Commercial | 2 | 75 | 203 | 280 |
| Household | 5 | 78 | 197 | 280 |
| Hazardous | 0 | 5 | 275 | 280 |
| Liquids/Sludge | 0 | 28 | 253 | 280 |
| Total | 74 (26.43%) | 145 (51.78%) | 61 (21.79%) | 280 (100%) |

Table 3.14 shows the frequency of historical landfill sites within 5 km from the property which had taken gas control and leachate control measures. Gas control measures[59] may include venting landfill gas, mainly methane and carbon dioxide, or burning it off. It is also necessary to use leachate control methods such as borehole pumps for extracting the leachate in order to prevent groundwater pollution. It is not clear whether historical landfill sites have neither gas nor leachate control measures in place since that data suffers from large

[58] Refer to Appendix 3.3 for the definition of each waste type.

[59] Refer to Appendix 3.4 for more information about each waste control measure.

proportion of missing values.

**Table 3.14: Control measures**

| Control measures | Frequency | Percent |
|---|---|---|
| Gas control | 36 | 12.08 |
| Leachate control | 3 | 1.07 |

Table 3.15 shows active landfills classified using A-code defined by Regulation Information System for Waste Management (REGIS). While none of the active sites is specialised in household, commercial and hazardous waste, there are three co-disposal sites. More than half of the active landfills specialised in non-biodegradable waste which does not include waste from construction. Restricted-user landfill or landfill known as 'factory-curtilage landfill' refers to industrial landfill sites owned by the waste producer or restricted to specific users.

**Table 3.15: Waste type buried in active sites**

| Waste type | Frequency | Percent |
|---|---|---|
| A01 (Co-disposal) | 3 | 18.75 |
| A05 (Non-biodegradable waste (not construction)) | 9 | 56.25 |
| A06 (Other waste (construction, demolition and dredgings)) | 3 | 18.75 |
| A07 (Restricted industrial waste) | 1 | 6.25 |
| Total | 16 | 100.00 |

Table 3.16 and 3.17 shows the number of years for which active landfill site and historical sites are operational. Of all 16 active sites within 5 km from the property, the earliest opening date is 1977. The average period of operation for active sites is about 10 years and the maximum is approximately 21 years. Of all 280 historical sites, the earliest opening date is 1895 which is located between 4 and 5 km from the nearest property. Within 4 km from the nearest property, the earliest date is 1904. Due to the lack of data either on opening or closing dates, data for about 40% of the studied sites are missing. Excluding these missing data, the average period of operation year is 14.84 years and the maximum year nearly 90 years.

**Table 3.16: Operation years of active sites**

| Number of years operated | Frequency | Percent | Cumulative percent |
|---|---|---|---|
| years≤5 | 4 | 25.00 | 25.00 |
| 5< years ≤10 | 6 | 37.50 | 62.50 |
| 10< years ≤20 | 4 | 25.00 | 87.50 |
| Over 20 | 2 | 12.50 | 100.00 |
| Average year | 9.81 | | |
| Maximum year | 20.54 | | |

**Table 3.17: Operation years of historical sites**

| Number of years operated | Frequency | Percent | Cumulative percent |
|---|---|---|---|
| years≤5 | 64 | 22.78 | 22.78 |
| 5< years ≤10 | 27 | 9.96 | 32.74 |
| 10< years ≤20 | 33 | 11.74 | 44.48 |
| 20< years ≤30 | 17 | 6.05 | 50.53 |
| 30< years ≤40 | 8 | 2.85 | 53.38 |
| 40< years ≤50 | 8 | 2.85 | 56.23 |
| Over 50 | 9 | 3.20 | 59.43 |
| Unknown | 114 | 40.57 | 100.00 |
| Average year | 14.84 | | |
| Maximum year | 89.06 | | |

Table 3.18 shows how long ago historical sites closed. The most recent year is 1995 and the oldest is 1937. On average, historical sites have been closed for about 15 years. As mentioned, there is no information on closing date for about one third of sites.

**Table 3.18: The last date waste accepted in historical sites**

| Closing date | Frequency | Percent | Cumulative percent |
|---|---|---|---|
| Pre 1950 | 2 | 0.71 | 0.71 |
| 1950 <date<1960 | 2 | 0.71 | 1.43 |
| 1960<date<1970 | 13 | 4.64 | 6.07 |
| 1970<date<1980 | 45 | 16.07 | 22.14 |
| 1980<date<1990 | 82 | 29.29 | 51.43 |
| <1997 | 41 | 14.64 | 66.07 |
| Unknown | 95 | 33.93 | 100.00 |
| Average year | 1982 | | |
| Oldest | 1937 | | |

Many of historical landfill sites have been subject to some remediation, generally the installation of gas venting systems to protect adjoining properties from off-site migration. Existing uses of historical sites vary from public open uses, agricultural uses, residential or commercial and industrial uses to other type of waste disposal sites. Some are not developed at all after closure.

Those sites owned by the Council are likely to change to public open space. The impact of individual historical sites may vary with existing uses. However, due to stigma-related damages, house prices may still reflect disamenity effects which in turn determine subsequent decision on land uses likely to be undesirable.

### 3.5 Estimation of the Hedonic Price Function

Conventionally, empirical specifications in previous hedonic studies focus on estimating the effect that proximity to the nearest open site has on residential property values. The basic hedonic model for disamenity impacts of landfill is thus:

$$\ln(P) = \alpha + \sum_k \beta_k Z_k + \gamma(Dist) \qquad \textbf{(3.8)}$$

where the dependent variable is the natural log of house prices. *Z* includes structural characteristics, neighbourhood characteristics, accessibility characteristics and environmental characteristics. The variable '*Dist*' is constructed as distance to the nearest active landfill for each house. The estimated coefficient on distance to disamenity sites like landfill will be positive and thus house prices increase when such sites lie further away from the house. In the semi-log model, the implicit price for each distance from landfill equals the estimated coefficient on *Dist*, $\gamma$ times the house price, *P*, that is:

$$\frac{\partial P}{\partial Dist} = \gamma \cdot P \qquad \textbf{(3.9)}$$

As explained earlier, when employing distance as a proxy for landfill disamenity effects, many studies assume a critical distance cut-off beyond which landfill impacts become negligible. For this reason the distance variable acquires a constant value once this distance has been reached.

The hedonic theory does not suggest a particular functional form for the hedonic price equation. However, the Box-Cox transformation is commonly proposed to test the most appropriate functional form among alternatives. As discussed in Halvorsen and Pollakowski (1981), the Box-Cox transformation nests other popular functional forms as special cases. The general form of the Box-Cox transformation is given:

$$Y^{\theta} = \begin{cases} \dfrac{Y^{\theta} - 1}{\theta} & \theta \neq 0 \\ \ln Y & \theta = 0 \end{cases}$$

$$X^{\lambda} = \begin{cases} \dfrac{X^{\lambda} - 1}{\lambda} & \lambda \neq 0 \\ \ln X & \lambda = 0 \end{cases} \qquad \textbf{(3.10)}$$

where $Y$ and $X$ are the dependent and (a vector of) independent variables respectively. $Y^{\theta}$ and $X^{\lambda}$ are the transformation of variables $Y$ and $X$ by the Box-Cox parameter $\theta$ and $\lambda$, respectively. The optimal values of transformation parameters are obtained with non-linear methods, such as maximum likelihood (ML). The Box-Cox obtains ML estimates according to:

$$\frac{Y^{\theta} - 1}{\theta} = \alpha + \sum \beta_k \frac{X_k^{\lambda} - 1}{\lambda} + \sum \delta_j V_j + \varepsilon \qquad \textbf{(3.11)}$$

where $\varepsilon \sim N(0, \sigma^2)$. Since the transformed variables must be strictly positive to be defined for all values of $\theta$ and $\lambda$, variables in the vector $V_j$ that contain zero are not transformed. A test of which functional form is acceptable may be performed by testing the restrictions corresponding to that functional form using a likelihood ratio (LR) test. The Box-Cox parameter values -1, 0 and 1 correspond to the reciprocal, the log, and no transformation. In the hedonic literature, the most frequently used forms are linear and semi-logarithmic functional forms because of their usefulness of convenient interpretation of coefficients. Thus, given untransformed explanatory variables, a Box-Cox transformation of the dependent variable is used to choose between the linear or natural logarithmic forms.

The estimates of $\theta$ and the results of the LR tests for various models are presented Table A3.5.4 in Appendix 3.5. The results show that neither semi-logarithmic nor the linear functional forms were accepted by LR tests. The estimates of $\theta$ range from 0.188 to 0.193. Since $\theta$ is always closer to 0 than to 1 in all models, semi-logarithmic specification could be the best alternative. Therefore, I report the results of the semi-log hedonic equations estimated by OLS in the following analysis. The dependent variable is the natural logarithm of selling price and all remaining variables are entered linearly. Thus, the coefficients can be interpreted as a proportionate change of house-sale price with a change of one unit in explanatory variables.

In estimating the disamenity effects of landfill, there are, following the previous literature, quite a few issues that must be addressed. Firstly, I need to examine the distance decay relationship as well as the spatial limit of landfill impacts. I create interaction terms between *Dist* and a dummy for each concentric zone around the house (i.e. 0-1 km, 1-2 km, 2-3 km distance from the nearest landfill etc).

Secondly, the downwind location of properties may intensify the disamenity effects from landfills. Therefore, relative angles from prevailing wind direction need to be somehow included in hedonic price equations.

Thirdly, the disamenity impacts of landfill may vary depending on landfill characteristics.

These may be captured by including in hedonic price equation site-specific characteristics like the volume or type of waste accepted and the period of operation. This is achieved by creating interaction terms between *Dist* and various dummies and continuous variables each denoting particular landfill characteristics.

Fourthly, there are only a few active sites but a significant number of historical sites near to each residential property in Birmingham. Given that the long-term stigma damage by landfill might be significant, not only active sites but also historical sites should be included in the hedonic analysis. The effects of active and historical sites can then be compared.

Finally, residential properties in Birmingham are very often near to more than one landfill sites. This seems inevitable in a densely populated area like the West Midlands. However, the majority of previous literature studied a single site or considered only the impact of the nearest site. In this study I will, in later specifications, choose the number of landfill sites in a given area to serve as a measure of disamenity impacts whilst at the same time differentiating between active and historical sites. I will even distinguish between historical sites according to their closing dates in order to examine the duration of disamenity impacts post closure of the landfill site

### 3.5.1 Active Landfill Sites

The purpose of the first empirical analysis is simply to test the null hypothesis that proximity to an active landfill does not decrease housing values while also examining the effects of site-specific characteristics using interaction terms. I estimate an equation of the form:

$$\ln(P) = \alpha + \sum_k \beta_k Z_k + \gamma(Dist) + \delta(Downwind) + \sum_m \varphi_m X_m \cdot (Dist) \qquad \textbf{(3.12)}$$

where *Dist* is distance to the nearest active landfill site and *Downwind* is the deviation of the house-site angle from prevailing downwind in absolute degrees. $X_m$ is a set of dummy variables created from categorical variables such as critical distance cut-off, type of site classified according to A-code and the number of years operated. Interaction terms are generated by multiplying each set of dummies with the distance variable. Table 3.19 defines the landfill variables created for Model 1.

**Table 3.19: Definition of distance band variables for Model 1**

| Variable | Definition |
|---|---|
| ***Dist*** | Distance to the nearest active site(km) |
| ***Downwind*** | Deviation in absolute degrees from the prevailing downwind direction |
| ***Zone· Dist*** | |
| (0-1 km)·*Dist* | Interaction between *Dist* and a dummy with 1 for *Dist* ≤ 1 km (baseline) |
| (1-2 km)· *Dist* | Interaction between *Dist* and a dummy with 1 for 1 km< *Dist* ≤ 2 km |
| (2-3 km)· *Dist* | Interaction between *Dist* and a dummy with 1 for 2 km< *Dist* ≤ 3 km |
| (3-4 km)· *Dist* | Interaction between *Dist* and a dummy with 1 for 3 km< *Dist* ≤ 4 km |
| (Over 4 km)· *Dist* | Interaction between *Dist* and a dummy with 1 for *Dist* > 4 km |
| ***Type· Dist*** | |
| A01· *Dist* | Interaction between *Dist* and a dummy with 1 for A01 (co-disposal) site and 0 for all other types (baseline) |
| A05· *Dist* | Interaction between *Dist* and a dummy with 1 for A05 (Non-biodegradable waste (not construction)) site and 0 for all other types |
| A06· *Dist* | Interaction between *Dist* and a dummy with the value 1 for A06 (Other waste (construction, demolition and dredgings)) site and 0 for all other types |
| A07· *Dist* | Interaction between *Dist* and a dummy with 1 for A07 (Restricted industrial waste (factory curtilage)) site and zero for all other types |
| **Year·** ***Dist*** | |
| (Year_5)· *Dist* | Interaction between *Dist* and a dummy with 1 for landfills operated for less than and equal to 5 years (baseline) |
| (Year_5-10)· *Dist* | Interaction between *Dist* and a dummy with 1 for landfills operated for greater than 5 years but less than and equal to 10 years. |
| (Year_over10)· *Dist* | Interaction between *Dist* and a dummy with 1 for landfills operated for over 10 years. |
| ***Operated_year*** | Operated years in decades |

Model 1.1 is the simplest one, including only *Dist*. Model 1.2 includes both *Dist* and

*Downwind*. Model 1.3 tests nonlinearity using interaction terms between *Dist* and dummies for five concentric zones (0-1 km, 1-2 km, 2-3 km, 3-4 km and greater than 4 km). The Model 1.4 includes interaction terms between *Dist* and dummies for type of waste accepted. Model 1.5 and Model 1.6 test whether landfills operated for a longer period of time have a larger disamenity impact on the property prices. This is done using either interaction terms between *Dist* and dummies categorising the number of years (less than 5 years, 5-10 years and over 10 years) or simply using the number of years for which the nearest active site is operational, *Operated_year*.

Model 1 is estimated using OLS and the results are reported in Table 3.20. The explanatory power of the hedonic house price equation is good with an adjusted $R^2$ ranging from 0.7629 to 0.7642 across different submodels. My findings are as follow.

**Table 3.20: Estimation results of Model 1**

**OLS**
**Total observation: 10,792 cross sections**
**Dependent variable: ln(property prices)**

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| ***Structural Variables*** | | | | | | |
| Floor area | 0.0041*** | 0.0042*** | 0.0042*** | 0.0042*** | 0.0042*** | 0.0042*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Garden area | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Sales Date | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Age | -0.0234*** | -0.0239*** | -0.0233*** | -0.0239*** | -0.0235*** | -0.0231*** |
| | (0.0035) | (0.0035) | (0.0035) | (0.0035) | (0.0035) | (0.0035) |
| Beds | 0.0088* | 0.0090* | 0.0084* | 0.0092* | 0.0093* | 0.0091* |
| | (0.0048) | (0.0048) | (0.0048) | (0.0048) | (0.0048) | (0.0048) |
| WCs | 0.0117** | 0.0115** | 0.0115** | 0.0112* | 0.0120** | 0.0116** |
| | (0.0058) | (0.0058) | (0.0058) | (0.0058) | (0.0058) | (0.0058) |
| Floors | -0.1507*** | -0.1512*** | -0.1508*** | -0.1501*** | -0.1512*** | -0.1510*** |
| | (0.0121) | (0.0121) | (0.0121) | (0.0120) | (0.0121) | (0.0121) |
| Garage | 0.0732*** | 0.0732*** | 0.0737*** | 0.0734*** | 0.0739*** | 0.0731*** |
| | (0.0062) | (0.0062) | (0.0062) | (0.0061) | (0.0062) | (0.0062) |
| Detached | 0.0191 | 0.0186 | 0.0200 | 0.0191 | 0.0182 | 0.0190 |
| Bungalow | (0.0246) | (0.0246) | (0.0246) | (0.0246) | (0.0246) | (0.0246) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Semi-Detached | -0.0921*** | -0.0909*** | -0.0931*** | -0.1003*** | -0.0965*** | -0.0924*** |
| Bungalow | (0.0284) | (0.0284) | (0.0284) | (0.0284) | (0.0284) | (0.0284) |
| End Terrace | -0.2486** | -0.2447** | -0.2501** | -0.2393** | -0.2454** | -0.2461** |
| Bungalow | (0.1059) | (0.1059) | (0.1058) | (0.1056) | (0.1057) | (0.1059) |
| Terrace | -0.0975 | -0.1027 | -0.1014 | -0.1100 | -0.1073 | -0.0989 |
| Bungalow | (0.1360) | (0.1360) | (0.1359) | (0.1356) | (0.1358) | (0.1359) |
| Detached House | 0.1290*** | 0.1277*** | 0.1292*** | 0.1283*** | 0.1286*** | 0.1291*** |
| | (0.0095) | (0.0095) | (0.0095) | (0.0095) | (0.0095) | (0.0095) |
| End Terrace | -0.0874*** | -0.0873*** | -0.0874*** | -0.0883*** | -0.0885*** | -0.0879*** |
| House | (0.0084) | (0.0084) | (0.0084) | (0.0084) | (0.0084) | (0.0084) |
| Terrace House | -0.0989*** | -0.0995*** | -0.0985*** | -0.0985*** | -0.0992*** | -0.0991*** |
| | (0.0074) | (0.0074) | (0.0074) | (0.0074) | (0.0074) | (0.0074) |
| BG1 | -0.0468 | -0.0444 | -0.0469 | -0.0435 | -0.0543 | -0.0481 |
| | (0.1176) | (0.1176) | (0.1176) | (0.1173) | (0.1175) | (0.1176) |
| BG2 | 0.2369*** | 0.2355*** | 0.2373*** | 0.2408*** | 0.2418*** | 0.2344*** |
| | (0.0842) | (0.0841) | (0.0841) | (0.0839) | (0.0841) | (0.0841) |
| BG3 | -0.0861*** | -0.0849*** | -0.0835*** | -0.0851*** | -0.0870*** | -0.0854*** |
| | (0.0190) | (0.0190) | (0.0190) | (0.0189) | (0.0190) | (0.0190) |
| BG4 | -0.0236* | -0.0227 | -0.0220 | -0.0224 | -0.0238* | -0.0234* |
| | (0.0140) | (0.0140) | (0.0140) | (0.0140) | (0.0140) | (0.0140) |
| BG5 | 0.0595* | 0.0604* | 0.0637* | 0.0589* | 0.0602* | 0.0591* |
| | (0.0330) | (0.0330) | (0.0330) | (0.0329) | (0.0329) | (0.0330) |
| BG8 | 0.0737*** | 0.0741*** | 0.0805*** | 0.0737*** | 0.0743*** | 0.0733*** |
| | (0.0200) | (0.0200) | (0.0201) | (0.0200) | (0.0200) | (0.0200) |
| BG9 | 0.0809*** | 0.0808*** | 0.0811*** | 0.0857*** | 0.0809*** | 0.0812*** |
| | (0.0283) | (0.0283) | (0.0283) | (0.0282) | (0.0283) | (0.0283) |
| BG10 | -0.3299*** | -0.3305*** | -0.3296*** | -0.3295*** | -0.3322*** | -0.3324*** |
| | (0.0452) | (0.0452) | (0.0452) | (0.0451) | (0.0452) | (0.0452) |
| BG19 | 0.1033*** | 0.1041*** | 0.1029*** | 0.1102*** | 0.1072*** | 0.1038*** |
| | (0.0236) | (0.0236) | (0.0236) | (0.0235) | (0.0236) | (0.0236) |
| BG20 | -0.1022*** | -0.1024*** | -0.1012*** | -0.0972*** | -0.0985*** | -0.1011*** |
| | (0.0096) | (0.0096) | (0.0096) | (0.0096) | (0.0096) | (0.0096) |
| BG24 | 0.1051*** | 0.1064*** | 0.1052*** | 0.1077*** | 0.1051*** | 0.1054*** |
| | (0.0212) | (0.0212) | (0.0212) | (0.0212) | (0.0212) | (0.0212) |
| BG25 | -0.6560*** | -0.6561*** | -0.6494*** | -0.6636*** | -0.6713*** | -0.6563*** |
| | (0.1109) | (0.1108) | (0.1108) | (0.1106) | (0.1108) | (0.1108) |
| BG30 | -0.1258*** | -0.1265*** | -0.1267*** | -0.1313*** | -0.1276*** | -0.1264*** |
| | (0.0139) | (0.0139) | (0.0139) | (0.0139) | (0.0139) | (0.0139) |
| BG31 | -0.0576*** | -0.0597*** | -0.0556*** | -0.0592*** | -0.0573*** | -0.0561*** |
| | (0.0160) | (0.0160) | (0.0160) | (0.0160) | (0.0160) | (0.0160) |
| BG32 | 0.0534** | 0.0514** | 0.0538** | 0.0500** | 0.0500** | 0.0548** |
| | (0.0217) | (0.0217) | (0.0217) | (0.0217) | (0.0217) | (0.0217) |
| BG35 | 0.0290 | 0.0247 | 0.0278 | 0.0183 | 0.0196 | 0.0268 |
| | (0.0686) | (0.0686) | (0.0685) | (0.0684) | (0.0685) | (0.0686) |
| BG36 | -0.2349*** | -0.2352*** | -0.2336*** | -0.2377*** | -0.2348*** | -0.2329*** |
| | (0.0401) | (0.0400) | (0.0400) | (0.0400) | (0.0400) | (0.0400) |
| ***Neighbourhood Variables*** | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Age60 | 0.0004 | 0.0004 | 0.0003 | 0.0003 | 0.0004 | 0.0004 |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Unemployment | -0.0088*** | -0.0089*** | -0.0089*** | -0.0088*** | -0.0088*** | -0.0088*** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| White | 0.0040*** | 0.0040*** | 0.0040*** | 0.0040*** | 0.0040*** | 0.0039*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Asian | 0.0052*** | 0.0052*** | 0.0050*** | 0.0052*** | 0.0052*** | 0.0051*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Family with children | 0.0002 | 0.0001 | 0.0002 | 0.0000 | 0.0001 | 0.0002 |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| ***Accessibility Variables*** | | | | | | |
| Primary Schools | 0.1701*** | 0.1724*** | 0.1718*** | 0.1676*** | 0.1737*** | 0.1694*** |
| | (0.0173) | (0.0173) | (0.0174) | (0.0173) | (0.0173) | (0.0173) |
| Shops | -0.0106*** | -0.0102*** | -0.0097*** | -0.0104*** | -0.0104*** | -0.0105*** |
| | (0.0032) | (0.0032) | (0.0033) | (0.0032) | (0.0032) | (0.0032) |
| Rail Station | -0.0009*** | -0.0010*** | -0.0008*** | -0.0011*** | -0.0011*** | -0.0011*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Park | -0.0000 | -0.0001 | 0.0000 | 0.0000 | 0.0000 | -0.0000 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| University | -0.0022*** | -0.0021*** | -0.0022*** | -0.0026*** | -0.0024*** | -0.0023*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| CBD | 0.0005 | 0.0003 | 0.0006 | 0.0016 | -0.0001 | 0.0004 |
| | (0.0013) | (0.0013) | (0.0013) | (0.0014) | (0.0013) | (0.0013) |
| Motorway Junction | 0.0031*** | 0.0032*** | 0.0030*** | 0.0030*** | 0.0041*** | 0.0033*** |
| | (0.0011) | (0.0011) | (0.0011) | (0.0011) | (0.0011) | (0.0011) |
| Airport | -0.0075*** | -0.0075*** | -0.0076*** | -0.0079*** | -0.0076*** | -0.0076*** |
| | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) |
| Mosque | 0.0343*** | 0.0341*** | 0.0331*** | 0.0340*** | 0.0366*** | 0.0361*** |
| | (0.0043) | (0.0043) | (0.0043) | (0.0043) | (0.0043) | (0.0043) |
| Industry A | 0.0477*** | 0.0478*** | 0.0483*** | 0.0503*** | 0.0514*** | 0.0452*** |
| | (0.0046) | (0.0046) | (0.0046) | (0.0046) | (0.0046) | (0.0047) |
| Industry B | -0.0007 | -0.0013 | 0.0002 | -0.0056 | -0.0039 | 0.0023 |
| | (0.0068) | (0.0068) | (0.0068) | (0.0068) | (0.0069) | (0.0069) |
| Motorway | 0.0048 | 0.0041 | 0.0041 | 0.0018 | 0.0001 | 0.0032 |
| | (0.0050) | (0.0050) | (0.0050) | (0.0050) | (0.0051) | (0.0050) |
| Road A | -0.0235*** | -0.0235*** | -0.0227*** | -0.0248*** | -0.0241*** | -0.0232*** |
| | (0.0081) | (0.0081) | (0.0082) | (0.0081) | (0.0081) | (0.0081) |
| Road B | -0.0072 | -0.0068 | -0.0080 | -0.0063 | -0.0076 | -0.0066 |
| | (0.0063) | (0.0063) | (0.0063) | (0.0063) | (0.0063) | (0.0063) |
| Minor Road | -0.2715** | -0.2651** | -0.2619** | -0.2625** | -0.2803** | -0.2687** |
| | (0.1329) | (0.1329) | (0.1328) | (0.1326) | (0.1327) | (0.1328) |
| Railway | 0.0069 | 0.0081 | 0.0070 | 0.0162** | 0.0098 | 0.0089 |
| | (0.0070) | (0.0070) | (0.0070) | (0.0071) | (0.0070) | (0.0070) |
| ***Environmental Variables*** | | | | | | |
| Water View | 0.0000 | 0.0000 | 0.0001 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Park View | 0.0000 | -0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Road View | 0.0001 | 0.0000 | 0.0000 | 0.0001 | 0.0001 | 0.0001 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Rail View | -0.0020*** | -0.0020*** | -0.0020*** | -0.0018** | -0.0018** | -0.0019*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Road Noise | -0.0019*** | -0.0019*** | -0.0019*** | -0.0020*** | -0.0020*** | -0.0019*** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Rail Noise | -0.0022 | -0.0021 | -0.0021 | -0.0026 | -0.0028 | -0.0023 |
| | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) |
| Airport Noise | 0.0015 | 0.0015 | 0.0022 | -0.0000 | 0.0007 | 0.0002 |
| | (0.0026) | (0.0026) | (0.0026) | (0.0026) | (0.0026) | (0.0026) |
| $NO_2$ | 0.0006*** | 0.0006*** | 0.0005*** | 0.0004*** | 0.0005*** | 0.0006*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| CO | 0.0108 | 0.0105 | 0.0124* | 0.0125* | 0.0136** | 0.0097 |
| | (0.0067) | (0.0067) | (0.0067) | (0.0067) | (0.0068) | (0.0067) |
| ***Ward*** | | | | | | |
| Aston | -0.0580* | -0.0591* | -0.0740** | -0.0400 | -0.0587* | -0.0433 |
| | (0.0320) | (0.0320) | (0.0328) | (0.0320) | (0.0320) | (0.0324) |
| Bartley Green | -0.0605 | -0.0606 | -0.0716 | -0.0575 | -0.0571 | -0.0513 |
| | (0.0494) | (0.0494) | (0.0495) | (0.0494) | (0.0493) | (0.0495) |
| Billesley | 0.0608* | 0.0668** | 0.0656** | 0.0334 | 0.0462 | 0.0711** |
| | (0.0321) | (0.0322) | (0.0322) | (0.0323) | (0.0323) | (0.0323) |
| Bournville | 0.0876** | 0.0930** | 0.0808** | 0.0642 | 0.0831** | 0.0973** |
| | (0.0403) | (0.0404) | (0.0407) | (0.0405) | (0.0403) | (0.0405) |
| Brandwood | 0.0720* | 0.0765* | 0.0686* | 0.0407 | 0.0551 | 0.0801** |
| | (0.0392) | (0.0392) | (0.0393) | (0.0394) | (0.0395) | (0.0393) |
| Edgbaston | 0.1594*** | 0.1642*** | 0.1606*** | 0.1699*** | 0.1589*** | 0.1710*** |
| | (0.0388) | (0.0388) | (0.0389) | (0.0391) | (0.0388) | (0.0390) |
| Erdington | 0.1485*** | 0.1446*** | 0.1498*** | 0.1904*** | 0.1671*** | 0.1649*** |
| | (0.0278) | (0.0278) | (0.0278) | (0.0285) | (0.0280) | (0.0284) |
| Fox Hollies | 0.0158 | 0.0220 | 0.0174 | 0.0060 | 0.0084 | 0.0079 |
| | (0.0214) | (0.0215) | (0.0214) | (0.0215) | (0.0214) | (0.0216) |
| Hall Green | 0.0316 | 0.0367 | 0.0354 | 0.0186 | 0.0174 | 0.0310 |
| | (0.0243) | (0.0244) | (0.0244) | (0.0244) | (0.0244) | (0.0243) |
| Handsworth | -0.0067 | -0.0054 | 0.0102 | 0.0173 | -0.0058 | 0.0094 |
| | (0.0328) | (0.0328) | (0.0333) | (0.0329) | (0.0329) | (0.0333) |
| Harborne | 0.1934*** | 0.1985*** | 0.1866*** | 0.2235*** | 0.1945*** | 0.2025*** |
| | (0.0446) | (0.0446) | (0.0446) | (0.0446) | (0.0446) | (0.0447) |
| Hodge Hill | 0.1283*** | 0.1270*** | 0.1259*** | 0.1628*** | 0.1407*** | 0.1489*** |
| | (0.0277) | (0.0277) | (0.0277) | (0.0284) | (0.0281) | (0.0287) |
| King's Norton | 0.0659 | 0.0703 | 0.0620 | 0.0234 | 0.0747 | 0.0755 |
| | (0.0470) | (0.0470) | (0.0471) | (0.0474) | (0.0470) | (0.0471) |
| Kingsbury | 0.1607*** | 0.1583*** | 0.1584*** | 0.1851*** | 0.1553*** | 0.1849*** |
| | (0.0347) | (0.0347) | (0.0349) | (0.0348) | (0.0354) | (0.0357) |
| Kingstanding | 0.0976*** | 0.0916*** | 0.0938*** | 0.1256*** | 0.1042*** | 0.1155*** |
| | (0.0323) | (0.0323) | (0.0323) | (0.0329) | (0.0324) | (0.0329) |
| Ladywood | 0.0446 | 0.0493 | 0.0475 | 0.0814** | 0.0571 | 0.0570 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.0374) | (0.0374) | (0.0374) | (0.0376) | (0.0375) | (0.0376) |
| Longbridge | 0.1437*** | 0.1536*** | 0.1491*** | 0.1258*** | 0.1584*** | 0.1538*** |
| | (0.0455) | (0.0456) | (0.0455) | (0.0457) | (0.0455) | (0.0456) |
| Moseley | 0.1726*** | 0.1782*** | 0.1674*** | 0.1908*** | 0.1837*** | 0.1911*** |
| | (0.0356) | (0.0356) | (0.0356) | (0.0359) | (0.0357) | (0.0362) |
| Nechells | 0.0986*** | 0.1037*** | 0.1016*** | 0.1189*** | 0.1023*** | 0.1130*** |
| | (0.0306) | (0.0306) | (0.0308) | (0.0307) | (0.0307) | (0.0310) |
| Northfield | 0.0426 | 0.0475 | 0.0428 | 0.0091 | 0.0611 | 0.0547 |
| | (0.0436) | (0.0436) | (0.0436) | (0.0439) | (0.0437) | (0.0438) |
| Oscott | 0.0070 | 0.0060 | 0.0041 | 0.0115 | -0.0073 | 0.0188 |
| | (0.0348) | (0.0348) | (0.0348) | (0.0350) | (0.0349) | (0.0351) |
| Perry Barr | -0.0460 | -0.0477 | -0.0441 | -0.0498 | -0.0707** | -0.0429 |
| | (0.0340) | (0.0340) | (0.0342) | (0.0340) | (0.0343) | (0.0340) |
| Quinton | 0.0328 | 0.0334 | 0.0255 | 0.0792* | 0.0354 | 0.0460 |
| | (0.0463) | (0.0462) | (0.0463) | (0.0466) | (0.0463) | (0.0465) |
| Sandwell | -0.0234 | -0.0218 | -0.0185 | -0.0342 | -0.0409 | -0.0206 |
| | (0.0313) | (0.0313) | (0.0314) | (0.0313) | (0.0314) | (0.0313) |
| Selly Oak | 0.1176*** | 0.1223*** | 0.1115*** | 0.1381*** | 0.1330*** | 0.1288*** |
| | (0.0414) | (0.0414) | (0.0416) | (0.0418) | (0.0415) | (0.0416) |
| Shard End | 0.0453 | 0.0410 | 0.0399 | 0.0663** | 0.0382 | 0.0652** |
| | (0.0320) | (0.0321) | (0.0321) | (0.0322) | (0.0326) | (0.0328) |
| Sheldon | -0.0187 | -0.0177 | -0.0165 | -0.0118 | -0.0141 | -0.0228 |
| | (0.0229) | (0.0229) | (0.0232) | (0.0229) | (0.0229) | (0.0230) |
| Small Heath | 0.0407* | 0.0467** | 0.0495** | 0.0639*** | 0.0531** | 0.0551** |
| | (0.0226) | (0.0227) | (0.0230) | (0.0229) | (0.0229) | (0.0232) |
| Soho | -0.2263*** | -0.2256*** | -0.2208*** | -0.2039*** | -0.2171*** | -0.2106*** |
| | (0.0327) | (0.0327) | (0.0329) | (0.0329) | (0.0328) | (0.0332) |
| Sparkbrook | -0.0265 | -0.0145 | -0.0185 | -0.0088 | -0.0231 | -0.0116 |
| | (0.0324) | (0.0327) | (0.0327) | (0.0325) | (0.0325) | (0.0328) |
| Sparkhill | 0.0515* | 0.0582** | 0.0579** | 0.0762*** | 0.0676** | 0.0658** |
| | (0.0289) | (0.0290) | (0.0290) | (0.0293) | (0.0292) | (0.0294) |
| Stockland Green | 0.0723** | 0.0678** | 0.0732** | 0.1041*** | 0.0807*** | 0.0901*** |
| | (0.0295) | (0.0296) | (0.0297) | (0.0299) | (0.0297) | (0.0302) |
| Sutton Four | 0.4777*** | 0.4698*** | 0.4757*** | 0.5044*** | 0.4942*** | 0.4962*** |
| Oaks | (0.0415) | (0.0416) | (0.0416) | (0.0424) | (0.0417) | (0.0420) |
| Sutton New Hall | 0.3892*** | 0.3820*** | 0.3852*** | 0.4196*** | 0.3722*** | 0.4241*** |
| | (0.0317) | (0.0317) | (0.0318) | (0.0318) | (0.0338) | (0.0341) |
| Sutton Vesey | 0.2763*** | 0.2691*** | 0.2745*** | 0.3167*** | 0.2833*** | 0.2952*** |
| | (0.0308) | (0.0309) | (0.0308) | (0.0315) | (0.0311) | (0.0315) |
| Washwood | 0.0306 | 0.0316 | 0.0290 | 0.0551** | 0.0375 | 0.0479* |
| Heath | (0.0262) | (0.0262) | (0.0265) | (0.0264) | (0.0264) | (0.0270) |
| Weoley | -0.0428 | -0.0396 | -0.0515 | -0.0767* | -0.0338 | -0.0315 |
| | (0.0438) | (0.0438) | (0.0440) | (0.0441) | (0.0438) | (0.0440) |
| Yardley | 0.0405* | 0.0381* | 0.0425** | 0.0501** | 0.0426** | 0.0394* |
| | (0.0212) | (0.0212) | (0.0212) | (0.0212) | (0.0212) | (0.0212) |
| ***Landfill Variables*** | | | | | | |
| *Dist* | 0.0114*** | 0.0124*** | 0.0576 | -0.0009 | 0.0205*** | 0.0116*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.0044) | (0.0044) | (0.0681) | (0.0048) | (0.0050) | (0.0044) |
| *Downwind* | | 0.0001*** | | | | |
| | | (0.0001) | | | | |
| (1-2 km)· *Dist* | | | -0.0058 | | | |
| | | | (0.0644) | | | |
| (2-3 km)· *Dist* | | | -0.0462 | | | |
| | | | (0.0655) | | | |
| (3-4 km)· *Dist* | | | -0.0381 | | | |
| | | | (0.0663) | | | |
| (Over 4 km)· *Dist* | | | -0.0423 | | | |
| | | | (0.0667) | | | |
| A05· *Dist* | | | | 0.0162*** | | |
| | | | | (0.0025) | | |
| A06· *Dist* | | | | -0.0009 | | |
| | | | | (0.0074) | | |
| A07· *Dist* | | | | 0.0065*** | | |
| | | | | (0.0024) | | |
| (Year_5-10)· *Dist* | | | | | -0.0136*** | |
| | | | | | (0.0032) | |
| (Year_over10)· *Dist* | | | | | -0.0067** | |
| | | | | | (0.0032) | |
| *Operated year* | | | | | | 0.0024*** |
| | | | | | | (0.0009) |
| Constant | 10.516*** | 10.493*** | 10.493*** | 10.577*** | 10.559*** | 10.507*** |
| | (0.0910) | (0.0914) | (0.0926) | (0.0914) | (0.0913) | (0.0911) |
| ***Diagnostic tests*** | | | | | | |
| N | 10792 | 10792 | 10792 | 10792 | 10792 | 10792 |
| $R^2$ | 0.7651 | 0.7653 | 0.7655 | 0.7664 | 0.7657 | 0.7653 |
| Adjusted $R^2$ | 0.7629 | 0.7630 | 0.7632 | 0.7642 | 0.7635 | 0.7630 |
| AIC | -681.1632 | -686.9096 | -692.5364 | -737.4111 | -707.1386 | -686.9205 |
| Jarque-bera | 4931*** | 4924 | 4955*** | 5063*** | 4936 | 4941*** |
| Multicollinearity | 0.23490291 | 0.23473436 | 0.2344816 | 0.2335519 | 0.23425135 | 0.23473412 |
| Breusch-Pagan | 0.29 | 0.18 | 0.07 | 0.53 | 0.23 | 0.18 |
| Ramsey RESET | 54.58*** | 54.94*** | 54.76*** | 53.89*** | 54.59*** | 55.52*** |

*Notes*: *Dist* is the baseline in Model 1.3, 1.4 and 1.5 representing (0-1km) ·*Dist*, A01· *Dist* and (Year_5) · *Dist* respectively. Standard errors are in parentheses. Semi-detached houses, BG21 (Standard houses 1919-45), proportion of black residents and houses located in Acock's Green are omitted as baseline. Significance is indicated by *, **, *** for 0.1, 0.05 and 0.001 level, respectively. AIC is the Akaike Information Criterion (1974). Jarque-Bera (JB) is a test for normality. The null is normally distributed error terms. Multicollinearity is examined using the Variance Inflation Factors (VIFs). The 1/VIF column is the Tolerance. The VIF ranges from 1.0 to infinity. VIFs greater than 10.0 are generally seen as indicative of severe multicollinearity. Tolerance ranges from 0.0 to 1.0, with 1.0 being the absence of multicolinearity. Breusch-Pagan tests the null hypothesis that the error variances are all equal versus the alternative that the error variances are a multiplicative function of one or more variables. The Ramsey Regression Equation Specification Error Test (RESET) test (Ramsey, 1969) is a general specification test for the linear regression model, testing whether non-linear combinations of the explanatory variables have any power in explaining the exogenous variable. If non-linear combinations of the estimated values are statistically significant, the linear model is misspecified.

Most of structural characteristics are statistically significant at the 1% level and have a priori expected signs. The size of houses is controlled by the area of floor measured in square metre. House prices increase by about 0.4% per square metre increase in house sizes. The size of the garden area is also positively correlated with house prices, increasing by 0.04% per square metre. The number of bedrooms and bathrooms are less significant compared to other structural characteristics. However, estimates for those variables should be interpreted with caution since I already control the size of the house.

The number of floors accounts for a relatively large percentage change in property prices. It shows people prefer 2 storey houses to 3 storey houses, other things being equal. House prices decrease by 15% for every one floor extra. The age of house is another negative factor, decreasing house prices by around 2% per decade. The presence of a garage adds 7% to house prices. A positive coefficient on sales date marks a gradual increase in property prices over the year.

Property types also appear important in explaining house prices. Semi-detached houses are taken as the baseline property type and thus coefficients on other property types can be interpreted as the difference in price between that property type and a semi-detached house. The results show that most house types are cheaper than a semi-detached house. In particular, end terrace bungalows lower prices by 25%. Only detached houses are more expensive by 13% than the baseline type. The beacon group (BG) further explains the variation in house prices based on the age, size and architectural type of a property. BG21 (standard houses 1945-1953) is taken as the baseline. Most of the categorical dummy variables for BG are statistically significant. Houses of BG25 (individual houses 1919-1945) show a largest difference in prices, with a 66% reduction below the baseline type whilst BG2 (renovated cottage pre 1919) are 24% more expensive than the baseline BG.

Regarding neighbourhood variables, unemployment and an increase in the presence of certain ethnic groups in the surrounding area are highly related to property values. At the ED neighbourhood scale, unemployment in a district reduces property prices by 0.08% per 1% increase in unemployment rate. For ethnicity, the percent of black population in each ED is taken as the baseline. Compared to that baseline, the more a neighbourhood is populated by whites and Asians, the higher property prices. However, it might be surprising that Asian population fetches higher population than white population.[60] Other neighbourhood variables such as family composition and age composition of a district do not show any statistically significant relationship with house prices.

A dummy for each ward is also estimated as an attempt to include unidentified characteristics of neighbourhood. The baseline ward is Acock's Green. Compared to the baseline ward, many wards in Birmingham have significantly higher property prices. Of those, Sutton Four Oaks is the most expensive area with 50% higher property values while houses in Soho are about 22% cheaper than in Acock's Green. This shows big divergence in house prices across wards in Birmingham.

The sign of the coefficients on the accessibility variables indicates whether the sites are an amenity or disamenity. Since the variables are measured either in terms of distance or travel times, a positive sign implies the further away from the sites, the higher prices of houses. Therefore, a positive coefficient indicates a disamenity. The results show that the motorway junction, mosque and Industry A are disamenities. With each minute less of driving to motorway junction, the price diminishes by 0.3%. The coefficients on mosque and Industry A

[60] Bateman et al. (2004) compare homogeneity of ethnicity across submarkets in Birmingham and find that house prices decrease as ethnic minority increases. This suggests that people prefer ethnic homogeneity amongst residents.

point to a 3% and 5% increase in house prices per km further away from those sites respectively. However, the distance to the CBD and park, both commonly used accessibility variables in previous studies, are statistically insignificant. The negative coefficient on shops implies the bigger and the closer the local shopping centre the lower are house prices. Bateman et al. (2004) displays a varying impact of distance to local shops across submarkets. In particular, whether the proximity to shops is amenity or disamenity depends on the wealth of the residents in each submarket.

There is also strong evidence for the impact of school quality and accessibility on local house prices. The inverse distance weighted by primary school quality is positively related to house prices. Easier access to high quality schools lifts house prices. Accessibility to public transport and transport infrastructure, such as a railway station, airport and different types of road, in particular A roads and minor roads are also found to have positive impacts on house prices. Of these, the distance to the nearest minor road has the biggest impact on house prices, indicating a 27% price premium on properties per kilometre. A reduced walking distance to the University of Birmingham/Queen Elizabeth hospital also increases property prices by 0.2% per minute.

Parameter estimates for most environmental variables are insignificant except having a view of the railway and noise from the road. Holding all other factors constant, each square meter increase in rail view reduces property prices by 0.2%. Properties with exposure to noise levels greater than 55 dB also experience a decrease in price by 0.2% for each dB increase in road noise. However, air quality measured by $NO_2$ concentrations unexpectedly increases property prices. This may be due to a high correlation between air quality and wealth (as revealed by car ownership).

In general, the results for the non-landfill variables appear insensitive to different econometric models for landfills variables. Thus I will not discuss these further and instead focus attention wholly on the landfill variables. Turning now to the variables of chief interest Model 1.1 is a base specification only taking into account distance to the nearest active landfill. Greater distance has a positive impact, increasing the prices by 1.14% for each additional 1 km. Based on mean property values, this is equal to a £672.56 rise in house price, which is a rather small increase compared to other studies.

Model 1.2 adds the angle for downwind position. Both distance from the nearest site and angle from downwind variables are statistically significant at the 1% level of significance. The coefficient on distance however, increases somewhat showing a 1.24% price increase per 1 km from the site. The positive sign on *Downwind* suggests that prices are reduced when property is downwind of the nearest active landfill site. More specifically, results indicate that for every 1 degree deviation from downwind prices increase by 0.01%.

In Model 1.3, interaction terms are used to in effect test for the existence of a nonlinear relationship between distance and house prices. In Model 1.1 landfill impacts are depicted as continuously decaying over distance. However, such impacts may be nonlinear and moreover, there may be a critical distance beyond which further landfill impacts are entirely absent. To investigate this I create distance bands in 1 km increments up to 4 km based on previous studies most of which conclude that a 2-3 mile radius was adequate for capturing the geographically limited impacts of landfill disamenity. These are then intereacted with distance to the nearest active landfill. However, none of the interaction terms are statistically significant suggesting, possibly somewhat surprisingly, the absence of nonlinearity or a critical distance.

In Model 1.4, nearest active sites are classified into four types: A03 (co-disposal), A05 (non-biodegradable waste), A06 (other wastes) and A07 (industrial waste). The baseline type of waste is A03. A03 and A06 sites are found statistically insignificant while the coefficients on the interactive terms for A05 and A07 sites were statistically significant and positive at the 1% significance level. This implies that residents are sensitive to proximity to landfills if sites specialised in non-biodegradable waste and industrial waste. For these types of landfill prices increase by 1.71% and 0.74% per kilometre respectively. Considering the serious problems caused by non-biodegradable waste,[61] the results suggest that residents are aware of the risks related to living near potentially hazardous waste disposal sites.

Models 1.5 and 1.6 deal with further potentially important landfill characteristics, specifically the number of years for which they are operational. Firstly, three periods of operation are used to create interaction terms with *Dist*. The baseline, represented by *Dist* is for landfills operated for less than 5 years (describing nearly 50% of the nearest landfills to properties in the dataset). Such landfills reduce property prices by 2.05% for each kilometre closer to the site. Landfills operated for more than 5 years show smaller disamenity effects. Landfill impacts are between 0.69% and 1.38% respectively for landfills operated for 5-10 years and over 10 years. This shows that residents are more concerned about impacts from new landfills than more established landfills

Instead of discrete interaction terms, Model 1.6 includes the number of years operated as a continuous variable. This regression reveals a 1.16% reduction in the price per kilometre closer to the site. Similar to the Model 1.5, there is a positive relationship between prices and years operated for the nearest site. Property prices appreciate by 0.24% for every decade that the site is operational. Both regressions, thus, confirm the results of the study by Cambridge Econometrics et al. (2003) which also find that adverse impacts of landfill on property values

[61] Non-biodegradable waste is in-organic or man-made materials that will not be decomposed by natural processes. Some of these materials remain under the ground for 500 years, which have long-lasting effects on surrounding area as pollutants may eventually make their way down through the soil and into the groundwater.

are greater for ‘start up’ than more established landfills in England and Wales. The Cambridge Econometrics study shows that house prices are 10% lower for landfill sites operated for 0-10 years than those operated for 20-30 years. This may be because residents begin to anticipate the eventual closure and remediation of the site.

**Figure 3.10: Reduction in house prices over the years of landfill operated**

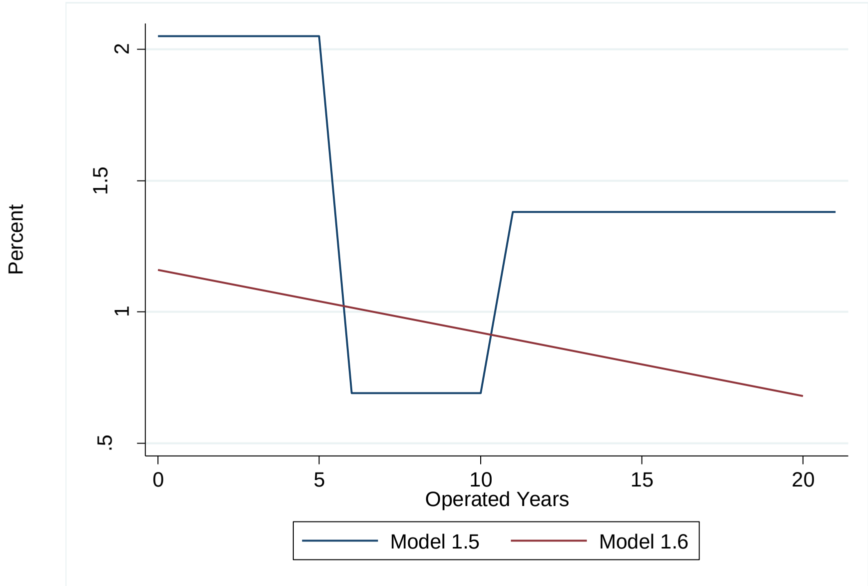



Figure 3.10 summarises a change in disamenity impacts over the years operated, using Models 1.5 and 1.6. Although landfills operated for over 10 years show greater impacts than those operated for 5-10 years, there is nevertheless a decrease in disamenity impacts as the landfill grows older.

### 3.5.2 Historical Landfill Sites

The purpose of this section is to extend the previous specification in order to compare the disamenity impact of historical and active landfill sites. This is achieved by creating a dummy variable for active sites and interacting it with distance. Therefore, Model 2 can be written as:

$$\ln(P) = \alpha + \sum_k \beta_k Z_k + \gamma_1(Dist) + \gamma_2(Active \cdot Dist) + \delta(Downwind) + \sum_m \varphi_m X_m \cdot (Dist) \quad \textbf{(3.13)}$$

Critically, *Dist* is the distance to the nearest historical landfill. *Active* is a dummy variable which is zero if the nearest landfill is a historical site and one if it is active. Thus *Active ·Dist* is the distance to the nearest active site. Out of 10,792 observations, the nearest landfill site is active for only 94 observations.

**Table 3.21: Definition of distance band variables for Model 2**

| Variable | Definition |
|---|---|
| ***Dist*** | Distance to the nearest site (km) |
| ***Active· Dist*** | Interaction between *Dist* and a dummy for active site |
| ***Downwind*** | Deviation in absolute degrees from the prevailing downwind direction |
| ***Zone· Dist*** | |
| (0-1 km)· *Dist* | Interaction between *Dist* and a dummy with 1 for *Dist* ≤ 1 km |
| (1-2 km)· *Dist* | Interaction between *Dist* and a dummy with 1 for 1 km< *Dist* ≤ 2 km |
| (2-3 km)· *Dist* | Interaction between *Dist* and a dummy with 1 for 2 km< *Dist* ≤ 3 km |
| (3-4 km)· *Dist* | Interaction between *Dist* and a dummy with 1 for 3 km< *Dist* ≤ 4 km |
| ***Type· Dist*** | |
| Inert· *Dist* | Interaction between *Dist* and a dummy with 1 for landfill which accepted inert waste |
| Industrial· *Dist* | Interaction between *Dist* and a dummy with 1 for landfill which accepted industrial waste |
| Commercial· *Dist* | Interaction between *Dist* and a dummy with 1 for landfill which accepted commercial waste |
| Household· *Dist* | Interaction between *Dist* and a dummy with 1 for landfill which accepted household waste |
| Hazardous· *Dist* | Interaction between *Dist* and a dummy with 1 for landfill which accepted hazardous waste |
| Liquids/Sludge· *Dist* | Interaction between *Dist* and a dummy with 1 for landfill which accepted liquids/sludge. |
| ***Co-disposal· Dist*** | Interaction between *Dist* and a dummy with 1 for landfill which accepted liquids/sludge. |
| **Year·** ***Dist*** | |
| (Year_5)· *Dist* | Interaction between *Dist* and a dummy with 1 for landfills operated for less than and equal to 5 years. |
| (Year_5-10)· *Dist* | Interaction between *Dist* and a dummy with 1 for landfills operated for more than 5 years but less than and equal to 10 years |
| (Year_10-20)· *Dist* | Interaction between *Dist* and a dummy with 1 for landfills operated for than 10 years but less than and equal to 20 years |

| | |
|---|---|
| (Year_over 20)· *Dist* | Interaction between *Dist* and a dummy with 1 for landfills operated for more than 20 years. |
| (Year_unknown)· *Dist* | Interaction between *Dist* and a dummy with 1 for landfills of which the number of years operated are unknown. |

Table 3.21 defines the landfill variables for Model 2. When historical sites are included more diverse types of waste are observed (requiring a different classification). Some historical sites moreover are operational for a significant period of time.

**Table 3.22: Estimation results of Model 2**

**OLS**
**Total observation: 10,792 cross sections**
**Dependent variable: ln (property prices)**

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| ***Structural Variables*** | | | | | | |
| Floor area | 0.0041*** | 0.0041*** | 0.0041*** | 0.0041*** | 0.0041*** | 0.0041*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Garden area | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Sales Date | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Age | -0.0225*** | -0.0226*** | -0.0228*** | -0.0224*** | -0.0220*** | -0.0225*** |
| | (0.0035) | (0.0035) | (0.0035) | (0.0035) | (0.0035) | (0.0035) |
| Beds | 0.0087* | 0.0088* | 0.0098** | 0.0088* | 0.0089* | 0.0090* |
| | (0.0048) | (0.0048) | (0.0048) | (0.0048) | (0.0048) | (0.0048) |
| WCs | 0.0109* | 0.0108* | 0.0104* | 0.0109* | 0.0109* | 0.0111* |
| | (0.0058) | (0.0058) | (0.0058) | (0.0058) | (0.0058) | (0.0058) |
| Floors | -0.1507*** | -0.1507*** | -0.1494*** | -0.1500*** | -0.1493*** | -0.1500*** |
| | (0.0121) | (0.0121) | (0.0120) | (0.0120) | (0.0120) | (0.0121) |
| Garage | 0.0734*** | 0.0734*** | 0.0736*** | 0.0732*** | 0.0726*** | 0.0737*** |
| | (0.0062) | (0.0062) | (0.0061) | (0.0062) | (0.0061) | (0.0062) |
| Detached | 0.0162 | 0.0166 | 0.0150 | 0.0141 | 0.0148 | 0.0164 |
| Bungalow | (0.0245) | (0.0245) | (0.0245) | (0.0245) | (0.0245) | (0.0245) |
| Semi-Detached | -0.0924*** | -0.0930*** | -0.0915*** | -0.0925*** | -0.0932*** | -0.0924*** |
| Bungalow | (0.0284) | (0.0284) | (0.0283) | (0.0284) | (0.0283) | (0.0284) |
| End Terrace | -0.2456** | -0.2452** | -0.2442** | -0.2410** | -0.2407** | -0.2436** |
| Bungalow | (0.1057) | (0.1057) | (0.1056) | (0.1056) | (0.1056) | (0.1057) |
| Terrace | -0.0904 | -0.0888 | -0.0891 | -0.0920 | -0.0877 | -0.0850 |
| Bungalow | (0.1357) | (0.1357) | (0.1356) | (0.1356) | (0.1356) | (0.1357) |
| Detached House | 0.1298*** | 0.1298*** | 0.1290*** | 0.1302*** | 0.1307*** | 0.1302*** |
| | (0.0095) | (0.0095) | (0.0095) | (0.0095) | (0.0095) | (0.0095) |
| End Terrace | -0.0874*** | -0.0871*** | -0.0872*** | -0.0862*** | -0.0865*** | -0.0870*** |
| House | (0.0084) | (0.0084) | (0.0084) | (0.0084) | (0.0084) | (0.0084) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Terrace House | -0.0997*** | -0.0995*** | -0.0989*** | -0.0997*** | -0.0999*** | -0.0995*** |
| | (0.0074) | (0.0074) | (0.0074) | (0.0074) | (0.0074) | (0.0074) |
| BG1 | -0.0392 | -0.0363 | -0.0371 | -0.0367 | -0.0415 | -0.0389 |
| | (0.1174) | (0.1174) | (0.1173) | (0.1173) | (0.1173) | (0.1174) |
| BG2 | 0.2372*** | 0.2382*** | 0.2368*** | 0.2303*** | 0.2314*** | 0.2380*** |
| | (0.0840) | (0.0840) | (0.0839) | (0.0840) | (0.0839) | (0.0840) |
| BG3 | -0.0898*** | -0.0898*** | -0.0893*** | -0.0902*** | -0.0928*** | -0.0898*** |
| | (0.0189) | (0.0189) | (0.0189) | (0.0190) | (0.0189) | (0.0190) |
| BG4 | -0.0251* | -0.0250* | -0.0259* | -0.0251* | -0.0257* | -0.0249* |
| | (0.0140) | (0.0140) | (0.0140) | (0.0140) | (0.0140) | (0.0140) |
| BG5 | 0.0605* | 0.0596* | 0.0641* | 0.0604* | 0.0614* | 0.0593* |
| | (0.0329) | (0.0329) | (0.0329) | (0.0329) | (0.0329) | (0.0329) |
| BG8 | 0.0773*** | 0.0772*** | 0.0738*** | 0.0793*** | 0.0808*** | 0.0764*** |
| | (0.0200) | (0.0200) | (0.0200) | (0.0200) | (0.0200) | (0.0200) |
| BG9 | 0.0776*** | 0.0763*** | 0.0755*** | 0.0766*** | 0.0759*** | 0.0788*** |
| | (0.0283) | (0.0283) | (0.0283) | (0.0282) | (0.0282) | (0.0283) |
| BG10 | -0.3340*** | -0.3324*** | -0.3334*** | -0.3241*** | -0.3306*** | -0.3328*** |
| | (0.0452) | (0.0452) | (0.0452) | (0.0452) | (0.0451) | (0.0453) |
| BG19 | 0.1046*** | 0.1047*** | 0.1070*** | 0.1043*** | 0.1041*** | 0.1042*** |
| | (0.0235) | (0.0235) | (0.0235) | (0.0235) | (0.0235) | (0.0235) |
| BG20 | -0.1001*** | -0.1000*** | -0.0995*** | -0.0980*** | -0.0977*** | -0.0995*** |
| | (0.0096) | (0.0096) | (0.0095) | (0.0096) | (0.0096) | (0.0096) |
| BG24 | 0.1082*** | 0.1081*** | 0.1089*** | 0.1088*** | 0.1072*** | 0.1072*** |
| | (0.0212) | (0.0212) | (0.0212) | (0.0212) | (0.0212) | (0.0212) |
| BG25 | -0.6576*** | -0.6559*** | -0.6622*** | -0.6460*** | -0.6495*** | -0.6549*** |
| | (0.1107) | (0.1107) | (0.1106) | (0.1106) | (0.1106) | (0.1107) |
| BG30 | -0.1232*** | -0.1231*** | -0.1241*** | -0.1214*** | -0.1214*** | -0.1215*** |
| | (0.0139) | (0.0139) | (0.0139) | (0.0139) | (0.0139) | (0.0139) |
| BG31 | -0.0550*** | -0.0552*** | -0.0541*** | -0.0543*** | -0.0536*** | -0.0551*** |
| | (0.0160) | (0.0160) | (0.0160) | (0.0160) | (0.0160) | (0.0160) |
| BG32 | 0.0553** | 0.0548** | 0.0580*** | 0.0528** | 0.0553** | 0.0548** |
| | (0.0216) | (0.0216) | (0.0216) | (0.0216) | (0.0216) | (0.0217) |
| BG35 | 0.0287 | 0.0288 | 0.0256 | 0.0307 | 0.0362 | 0.0278 |
| | (0.0685) | (0.0684) | (0.0684) | (0.0687) | (0.0684) | (0.0685) |
| BG36 | -0.2441*** | -0.2456*** | -0.2464*** | -0.2432*** | -0.2452*** | -0.2464*** |
| | (0.0400) | (0.0400) | (0.0400) | (0.0400) | (0.0400) | (0.0401) |
| ***Neighbourhood Variables*** | | | | | | |
| Age60 | 0.0003 | 0.0003 | 0.0003 | 0.0004 | 0.0003 | 0.0003 |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Unemployment | -0.0090*** | -0.0090*** | -0.0089*** | -0.0090*** | -0.0091*** | -0.0090*** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| White | 0.0047*** | 0.0047*** | 0.0047*** | 0.0045*** | 0.0047*** | 0.0046*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Asian | 0.0057*** | 0.0057*** | 0.0057*** | 0.0056*** | 0.0058*** | 0.0056*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Family with | 0.0001 | 0.0001 | 0.0000 | 0.0001 | 0.0000 | 0.0001 |
| children | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| ***Accessibility Variables*** | | | | | | |
| Primary Schools | 0.1613*** | 0.1612*** | 0.1584*** | 0.1650*** | 0.1627*** | 0.1638*** |
| | (0.0173) | (0.0173) | (0.0173) | (0.0173) | (0.0172) | (0.0173) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Shops | -0.0130*** | -0.0130*** | -0.0141*** | -0.0146*** | -0.0142*** | -0.0136*** |
| | (0.0032) | (0.0032) | (0.0032) | (0.0032) | (0.0032) | (0.0032) |
| Rail Station | -0.0009*** | -0.0010*** | -0.0010*** | -0.0009*** | -0.0010*** | -0.0010*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Park | -0.0000 | -0.0000 | -0.0001 | 0.0002 | 0.0002 | 0.0001 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| University | -0.0023*** | -0.0023*** | -0.0024*** | -0.0023*** | -0.0023*** | -0.0024*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| CBD | 0.0008 | 0.0008 | 0.0015 | 0.0000 | 0.0006 | 0.0009 |
| | (0.0013) | (0.0013) | (0.0014) | (0.0013) | (0.0013) | (0.0013) |
| Motorway | 0.0032*** | 0.0032*** | 0.0033*** | 0.0035*** | 0.0028** | 0.0035*** |
| Junction | (0.0011) | (0.0011) | (0.0011) | (0.0011) | (0.0011) | (0.0011) |
| Airport | -0.0067*** | -0.0068*** | -0.0074*** | -0.0064*** | -0.0064*** | -0.0071*** |
| | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) |
| Mosque | 0.0324*** | 0.0325*** | 0.0339*** | 0.0332*** | 0.0328*** | 0.0333*** |
| | (0.0042) | (0.0042) | (0.0042) | (0.0043) | (0.0042) | (0.0043) |
| Industry A | 0.0433*** | 0.0436*** | 0.0457*** | 0.0451*** | 0.0442*** | 0.0446*** |
| | (0.0044) | (0.0044) | (0.0045) | (0.0045) | (0.0044) | (0.0045) |
| Industry B | -0.0027 | -0.0032 | -0.0033 | -0.0045 | -0.0038 | -0.0034 |
| | (0.0068) | (0.0068) | (0.0068) | (0.0069) | (0.0068) | (0.0069) |
| Motorway | 0.0090* | 0.0090** | 0.0072 | 0.0069 | 0.0079* | 0.0080* |
| | (0.0046) | (0.0046) | (0.0047) | (0.0047) | (0.0046) | (0.0046) |
| Road A | -0.0267*** | -0.0271*** | -0.0274*** | -0.0284*** | -0.0281*** | -0.0276*** |
| | (0.0081) | (0.0081) | (0.0081) | (0.0081) | (0.0081) | (0.0081) |
| Road B | -0.0094 | -0.0090 | -0.0101 | -0.0084 | -0.0082 | -0.0085 |
| | (0.0063) | (0.0063) | (0.0063) | (0.0064) | (0.0063) | (0.0063) |
| Minor Road | -0.2601** | -0.2621** | -0.2715** | -0.2716** | -0.3050** | -0.2729** |
| | (0.1326) | (0.1326) | (0.1328) | (0.1327) | (0.1327) | (0.1328) |
| Railway | 0.0104 | 0.0105 | 0.0133* | 0.0085 | 0.0097 | 0.0112 |
| | (0.0068) | (0.0068) | (0.0069) | (0.0069) | (0.0068) | (0.0069) |
| ***Environmental Variables*** | | | | | | |
| Water View | 0.0000 | 0.0000 | 0.0001 | 0.0000 | 0.0000 | 0.0000 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Park View | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0000 | 0.0000 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Road View | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Rail View | -0.0019*** | -0.0019*** | -0.0020*** | -0.0019*** | -0.0020*** | -0.0019*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Road Noise | -0.0018*** | -0.0018*** | -0.0017*** | -0.0017*** | -0.0017*** | -0.0017*** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Rail Noise | -0.0021 | -0.0022 | -0.0022 | -0.0023 | -0.0021 | -0.0022 |
| | (0.0020) | (0.0020) | (0.0019) | (0.0019) | (0.0019) | (0.0020) |
| Airport Noise | 0.0027 | 0.0027 | 0.0023 | 0.0036 | 0.0024 | 0.0033 |
| | (0.0025) | (0.0025) | (0.0025) | (0.0026) | (0.0025) | (0.0026) |
| $NO_2$ | 0.0006*** | 0.0006*** | 0.0006*** | 0.0005*** | 0.0006*** | 0.0006*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| CO | 0.0116* | 0.0117* | 0.0123* | 0.0122* | 0.0134** | 0.0123* |
| | (0.0067) | (0.0067) | (0.0067) | (0.0067) | (0.0067) | (0.0067) |

| | | | | | | |
|---|---|---|---|---|---|---|
| ***Ward*** | | | | | | |
| Aston | -0.1018*** | -0.1002*** | -0.1109*** | -0.1225*** | -0.1221*** | -0.1023*** |
| | (0.0327) | (0.0327) | (0.0327) | (0.0331) | (0.0329) | (0.0329) |
| Bartley Green | -0.0398 | -0.0374 | -0.0591 | -0.0507 | -0.0504 | -0.0310 |
| | (0.0478) | (0.0478) | (0.0479) | (0.0478) | (0.0478) | (0.0482) |
| Billesley | 0.0405 | 0.0409 | 0.0328 | 0.0287 | 0.0298 | 0.0466 |
| | (0.0321) | (0.0321) | (0.0321) | (0.0322) | (0.0321) | (0.0325) |
| Bournville | 0.0923** | 0.0936** | 0.0887** | 0.0778* | 0.0803** | 0.0903** |
| | (0.0396) | (0.0396) | (0.0396) | (0.0398) | (0.0396) | (0.0398) |
| Brandwood | 0.0681* | 0.0703* | 0.0712* | 0.0628 | 0.0691* | 0.0754* |
| | (0.0391) | (0.0391) | (0.0393) | (0.0393) | (0.0391) | (0.0395) |
| Edgbaston | 0.1246*** | 0.1276*** | 0.1239*** | 0.1094*** | 0.1324*** | 0.1413*** |
| | (0.0394) | (0.0395) | (0.0399) | (0.0399) | (0.0394) | (0.0401) |
| Erdington | 0.1529*** | 0.1540*** | 0.1560*** | 0.1518*** | 0.1513*** | 0.1576*** |
| | (0.0273) | (0.0273) | (0.0272) | (0.0274) | (0.0272) | (0.0275) |
| Fox Hollies | -0.0202 | -0.0196 | -0.0101 | -0.0285 | -0.0264 | -0.0300 |
| | (0.0218) | (0.0218) | (0.0219) | (0.0221) | (0.0218) | (0.0221) |
| Hall Green | 0.0008 | 0.0013 | 0.0023 | -0.0165 | -0.0150 | 0.0080 |
| | (0.0245) | (0.0245) | (0.0245) | (0.0249) | (0.0247) | (0.0250) |
| Handsworth | -0.0183 | -0.0180 | -0.0240 | -0.0500 | -0.0527 | -0.0305 |
| | (0.0331) | (0.0331) | (0.0332) | (0.0343) | (0.0338) | (0.0334) |
| Harborne | 0.1927*** | 0.1952*** | 0.1759*** | 0.1709*** | 0.1864*** | 0.1970*** |
| | (0.0440) | (0.0441) | (0.0442) | (0.0445) | (0.0440) | (0.0443) |
| Hodge Hill | 0.1371*** | 0.1393*** | 0.1388*** | 0.1305*** | 0.1372*** | 0.1412*** |
| | (0.0271) | (0.0272) | (0.0271) | (0.0273) | (0.0271) | (0.0277) |
| King's Norton | 0.0632 | 0.0637 | 0.0584 | 0.0424 | 0.0435 | 0.0644 |
| | (0.0464) | (0.0464) | (0.0464) | (0.0468) | (0.0465) | (0.0466) |
| Kingsbury | 0.1675*** | 0.1687*** | 0.1690*** | 0.1636*** | 0.1627*** | 0.1710*** |
| | (0.0342) | (0.0342) | (0.0342) | (0.0343) | (0.0342) | (0.0344) |
| Kingstanding | 0.1043*** | 0.1051*** | 0.0998*** | 0.1119*** | 0.1067*** | 0.1133*** |
| | (0.0314) | (0.0314) | (0.0314) | (0.0317) | (0.0313) | (0.0317) |
| Ladywood | 0.0367 | 0.0394 | 0.0255 | 0.0033 | 0.0301 | 0.0469 |
| | (0.0373) | (0.0373) | (0.0373) | (0.0384) | (0.0372) | (0.0375) |
| Longbridge | 0.1179*** | 0.1215*** | 0.1210*** | 0.1078** | 0.1093** | 0.1242*** |
| | (0.0455) | (0.0455) | (0.0455) | (0.0456) | (0.0455) | (0.0465) |
| Moseley | 0.1553*** | 0.1560*** | 0.1622*** | 0.1363*** | 0.1453*** | 0.1626*** |
| | (0.0357) | (0.0357) | (0.0357) | (0.0360) | (0.0357) | (0.0367) |
| Nechells | 0.0803*** | 0.0835*** | 0.0837*** | 0.0716** | 0.0700** | 0.0873*** |
| | (0.0300) | (0.0301) | (0.0300) | (0.0301) | (0.0300) | (0.0302) |
| Northfield | 0.0351 | 0.0369 | 0.0361 | 0.0131 | 0.0324 | 0.0321 |
| | (0.0433) | (0.0433) | (0.0434) | (0.0438) | (0.0433) | (0.0436) |
| Oscott | 0.0228 | 0.0237 | 0.0184 | 0.0044 | 0.0069 | 0.0283 |
| | (0.0332) | (0.0332) | (0.0332) | (0.0336) | (0.0333) | (0.0334) |
| Perry Barr | -0.0325 | -0.0317 | -0.0368 | -0.0486 | -0.0464 | -0.0259 |
| | (0.0332) | (0.0332) | (0.0332) | (0.0335) | (0.0333) | (0.0335) |
| Quinton | 0.0416 | 0.0441 | 0.0257 | 0.0183 | 0.0355 | 0.0484 |
| | (0.0456) | (0.0456) | (0.0457) | (0.0461) | (0.0455) | (0.0458) |
| Sandwell | -0.0117 | -0.0107 | -0.0167 | -0.0297 | -0.0199 | -0.0180 |
| | (0.0308) | (0.0309) | (0.0309) | (0.0312) | (0.0309) | (0.0310) |
| Selly Oak | 0.1146*** | 0.1171*** | 0.1056** | 0.1116*** | 0.1129*** | 0.1226*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.0410) | (0.0410) | (0.0411) | (0.0411) | (0.0410) | (0.0412) |
| Shard End | 0.0640** | 0.0660** | 0.0631** | 0.0685** | 0.0756** | 0.0691** |
| | (0.0311) | (0.0311) | (0.0310) | (0.0319) | (0.0311) | (0.0318) |
| Sheldon | -0.0269 | -0.0266 | -0.0366 | -0.0025 | -0.0107 | -0.0241 |
| | (0.0229) | (0.0229) | (0.0230) | (0.0239) | (0.0232) | (0.0239) |
| Small Heath | 0.0500** | 0.0521** | 0.0520** | 0.0391* | 0.0448** | 0.0523** |
| | (0.0227) | (0.0227) | (0.0227) | (0.0228) | (0.0227) | (0.0228) |
| Soho | -0.2045*** | -0.2042*** | -0.2087*** | -0.2300*** | -0.2256*** | -0.2074*** |
| | (0.0321) | (0.0321) | (0.0321) | (0.0327) | (0.0324) | (0.0324) |
| Sparkbrook | -0.0293 | -0.0276 | -0.0270 | -0.0353 | -0.0288 | -0.0171 |
| | (0.0326) | (0.0326) | (0.0326) | (0.0327) | (0.0326) | (0.0331) |
| Sparkhill | 0.0627** | 0.0638** | 0.0606** | 0.0547* | 0.0624** | 0.0618** |
| | (0.0288) | (0.0289) | (0.0288) | (0.0290) | (0.0288) | (0.0291) |
| Stockland Green | 0.0675** | 0.0698** | 0.0638** | 0.0634** | 0.0680** | 0.0784*** |
| | (0.0294) | (0.0295) | (0.0295) | (0.0297) | (0.0294) | (0.0299) |
| Sutton Four Oaks | 0.4737*** | 0.4742*** | 0.4840*** | 0.4689*** | 0.4725*** | 0.4790*** |
| | (0.0414) | (0.0414) | (0.0414) | (0.0427) | (0.0413) | (0.0425) |
| Sutton New Hall | 0.3909*** | 0.3916*** | 0.3941*** | 0.3873*** | 0.3890*** | 0.3922*** |
| | (0.0305) | (0.0305) | (0.0305) | (0.0318) | (0.0305) | (0.0312) |
| Sutton Vesey | 0.2911*** | 0.2921*** | 0.2928*** | 0.2889*** | 0.2911*** | 0.2988*** |
| | (0.0285) | (0.0285) | (0.0285) | (0.0292) | (0.0285) | (0.0291) |
| Washwood Heath | 0.0065 | 0.0090 | 0.0063 | -0.0055 | 0.0026 | 0.0118 |
| | (0.0263) | (0.0263) | (0.0263) | (0.0265) | (0.0263) | (0.0265) |
| Weoley | -0.0350 | -0.0325 | -0.0482 | -0.0492 | -0.0494 | -0.0309 |
| | (0.0428) | (0.0428) | (0.0429) | (0.0431) | (0.0429) | (0.0431) |
| Yardley | 0.0329 | 0.0346* | 0.0252 | 0.0416** | 0.0351* | 0.0362* |
| | (0.0209) | (0.0209) | (0.0210) | (0.0210) | (0.0209) | (0.0212) |
| ***Landfill Variables*** | | | | | | |
| *Dist* | 0.0324*** | 0.0326*** | 0.0678*** | 0.0420*** | 0.0478*** | 0.0402*** |
| | (0.0055) | (0.0055) | (0.0125) | (0.0071) | (0.0064) | (0.0115) |
| *Active· Dist* | 0.0695*** | 0.0705*** | 0.0672*** | 0.0549*** | 0.0558*** | 0.0804*** |
| | (0.0205) | (0.0205) | (0.0205) | (0.0209) | (0.0207) | (0.0218) |
| *Downwind* | | 0.0001 | | | | |
| | | (0.0000) | | | | |
| (1-2 km)· *Dist* | | | -0.0160** | | | |
| | | | (0.0077) | | | |
| (2-3 km)· *Dist* | | | -0.0487*** | | | |
| | | | (0.0109) | | | |
| (3-4 km)· *Dist* | | | -0.0052 | | | |
| | | | (0.0213) | | | |
| Inert· *Dist* | | | | -0.0235*** | | |
| | | | | (0.0058) | | |
| Industrial· *Dist* | | | | 0.0053 | | |
| | | | | (0.0060) | | |
| Commercial· *Dist* | | | | -0.0169** | | |
| | | | | (0.0085) | | |
| Household· *Dist* | | | | -0.0024 | | |
| | | | | (0.0075) | | |
| Hazardous· *Dist* | | | | -0.0197 | | |
| | | | | (0.0247) | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Liquids/Sludge· *Dist* | | | | -0.0029 (0.0240) | | |
| Co-disposal· *Dist* | | | | | -0.0256*** (0.0053) | |
| (Year_5-10)· *Dist* | | | | | | -0.0172 (0.0125) |
| (Year_10-20)· *Dist* | | | | | | -0.0081 (0.0127) |
| (Year_over 20)· *Dist* | | | | | | -0.0175 (0.0112) |
| (Year_unknown)· *Dist* | | | | | | 0.0014 (0.0108) |
| Constant | 10.4569*** (0.0914) | 10.4476*** (0.0915) | 10.4691*** (0.0924) | 10.4863*** (0.0923) | 10.4649*** (0.0913) | 10.4809*** (0.0931) |
| ***Diagnostic tests*** | | | | | | |
| N | 10792 | 10792 | 10792 | 10792 | 10792 | 10792 |
| $R^2$ | 0.7660 | 0.7661 | 0.7666 | 0.7666 | 0.7665 | 0.7662 |
| Adjusted $R^2$ | 0.7638 | 0.7638 | 0.7643 | 0.7642 | 0.7643 | 0.7639 |
| AIC | -721.0687 | -721.7377 | -742.7703 | -735.9701 | -743.0153 | -721.6733 |
| Jarque-bera | 4896*** | 4877*** | 4963*** | 4896*** | 4844*** | 4879*** |
| Multicollinearity | 0.2339925 | 0.2339347 | 0.2333927 | 0.23341 | 0.2334739 | 0.2338061 |
| Breusch-Pagan | 0.29 | 0.30 | 0.30 | 0.73 | 0.48 | 0.31 |
| Ramsey RESET | 52.24*** | 52.18*** | 51.35*** | 52.02*** | 52.24*** | 52.43*** |

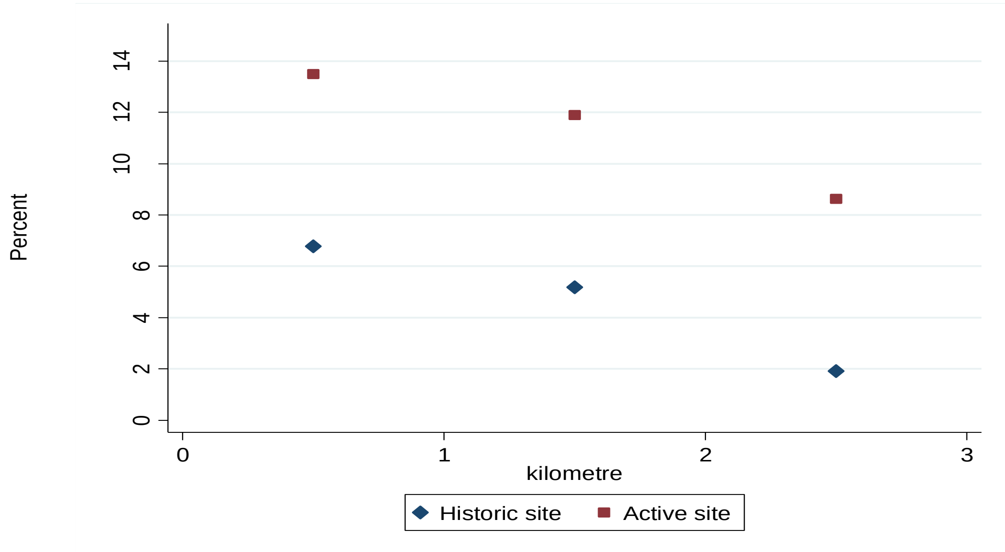
*Notes*: *Dist* is the distance to the nearest historical landfill sites. *Dist* is the baseline in Model 2.3, 2.4, 2.5 and 2.6 representing (0-1km)·*Dist*, (unknown waste type)·*Dist*, (single waste type)·*Dist* and (Year_5)·*Dist* respectively. Standard errors are in parentheses. See the notes for Table 3.20.

The results of Model 2 are reported in Table 3.22. The findings for non-landfill housing characteristics are consistent with those encountered in Model 1 and are therefore not discussed further. The most important finding is that historical sites do have impacts on property prices, which is largely ignored in previous studies. The coefficient both on *Dist* and *Active·Dist* is statistically significant and positive. This indicates substantial disamenity impact from the nearest historical landfills and an even greater disamenity impact if the landfill is currently active. Furthermore, the inclusion of historical sites increases the size of disamenity impacts from active landfill on property values. Every 1 km away from the nearest historical site increases house prices by 3.24% (on average £1,911). These results indicate that landfilling entails a long-term disamenity impact which endures even after sites are closed. The statistically significant and positive coefficient on *Active·Dist* confirms that active sites have a greater disamenity impact than historical sites, reducing property values by 10.2% (on average of £6,011) for each additional 1 km away from the nearest landfill site. This is much bigger than the result obtained in Model 1. This huge difference illustrates the importance of accounting for the potential disamenity impacts of historical sites.

In Model 2.2, the variable *Downwind* is included but is statistically insignificant. This may be because there is no airborne pollution from what are now predominantly historical landfill sites.

In Model 2.3, the coefficient on *Dist* reveals landfill disamenity impacts on those properties located within 1 km from the nearest historical site. But unlike the results from Model 1.3 there now appears to be several distinct breaks in the hedonic price gradient over three discrete distance ranges (0-1 km, 1-2 km and 2-3 km). The disamenity impact from historical landfill results in a 6.78%, 5.18% and 1.91% increase in house prices per kilometre measured within 0-1 km, 1-2 km and 2-3 km distance bands. Figure 3.11 summarises changes in magnitude of disamenity impacts over distance for both active and historical sites.

**Figure 3.11: Reductions in house prices over distance**



Model 2.4 attempts to differentiate landfill externalities according to type of waste accepted; inert, industrial, commercial, household hazardous waste and liquids/sludge. Compared to the results of Model 2.1, the disamenity impact of historical sites increases while the disamenity impact of active sites declines, reducing property values by 5.49% for every kilometre closer to the site. Overall it appears that disamenity impacts do not vary much with the types of waste accepted except for inert and commercial waste. The baseline is for waste of unknown type. In comparison to landfills accepting waste of unknown type, landfills accepting inert and commercial waste have a significantly smaller impact on property values. Note that these dummy variables for each type of waste do not exclude the possibility of the landfill also accepting other types of waste.

Model 2.5 includes an interaction term for co-disposal sites. The disposal of more than one category of waste in the same landfill site can be dangerous and partly for this reason co-disposal of non-hazardous and hazardous waste has now been banned by the Landfill Directive (EU Council Directive 1999/31/EC of 26 April 1999 on the Landfill of Waste). Landfills identified as taking more than one type of waste are therefore expected to have a more pronounced impact on property values. However, the results show that proximity to co-disposal landfills has a lesser impact on property prices than single waste type landfills.

Model 2.6 investigates the period of operation of historical and active landfills. The variable, *Dist* here represents distance to landfills operated for less than 5 years. None of interaction terms show statistically significant results. In other words, the disamenity impact from landfills does not vary according to the period of operation.

### 3.5.3 The Effects of Proximity to Multiple Sites

The next step of the current empirical approach is to account for the existence of proximity to multiple landfill sites near to each residential property. Thus, the third model is specified to include impacts of all landfill sites located within a given distance from the house. Four distance bands are created: 0-1 km, 1-2 km, 2-3 km and 3-4 km. Such an approach is preferable to one which includes the distance to each and every landfill sites which would contain too many variables. Separate distance band variables are created for active and historical sites. Furthermore, the number of historical sites is split into four variables according to how long ago they were closed. Model 3 can be represented as:

$$\ln(P) = \alpha + \sum_k \beta_k Z_k + \gamma Active_i + \sum_j \delta_j Historic_{ij} \qquad \textbf{(3.14)}$$

where $i$ indexes the distance band, $i$=(0-1, 0-2, 0-3, 0-4) and $j$ is a particular period of time during which the historical landfill closed.

Model 3 is separately estimated for each value of $i$ to identify the most appropriate boundary for landfill disamenity impacts. $Active_i$ is the number of active sites within distance band $i$. $Historic_{i1}$ is the number of historical sites closed 1-10 years ago, $Historic_{i2}$ is the number of historical sites closed 11-20 years ago, $Historic_{i3}$ is the number of historical sites closed over 20 years ago and $Historic_{i4}$ is the number of historical sites closed on an unknown dates. The coefficients on the landfill variables now represent the impact on property prices per landfill site within a boundary. Table 3.23 provides descriptive statistics for the landfill variables used in Model 3. Table 3.24 displays the estimation results of Model 3.

**Table 3.23: Definition of distance band variables for Model 3**

| Variable | Definition | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Distance band *i*=0-1 km** | | | | | |
| $Active_1$ | Number of active sites | 0 | 0.04 | 0 | 1 |
| $Historic_{11}$ | Number of historical sites closed *j*=1-10 years ago | 0.13 | 0.37 | 0 | 3 |
| $Historic_{12}$ | Number of historical sites closed *j*=11-20 years ago | 0.16 | 0.41 | 0 | 2 |
| $Historic_{13}$ | Number of historical sites closed *j*=over 20 years ago | 0.41 | 0.61 | 0 | 3 |
| $Historic_{14}$ | Number of historical sites closed *j*=on unknown dates | 0.29 | 0.59 | 0 | 3 |

| | | | | | |
|---|---|---|---|---|---|
| **Distance band *i*=0-2 km** | | | | | |
| *Active* $_2$ | Number of active sites | 0.03 | 0.17 | 0 | 1 |
| *Historic* $_{21}$ | Number of historical sites closed *j*=1-10 years ago | 0.53 | 0.78 | 0 | 5 |
| *Historic* $_{22}$ | Number of historical sites closed *j*=11-20 years ago | 0.70 | 0.90 | 0 | 4 |
| *Historic* $_{23}$ | Number of historical sites closed *j*=over 20 years ago | 1.56 | 1.26 | 0 | 6 |
| *Historic* $_{24}$ | Number of historical sites closed *j*=on unknown dates | 1.22 | 1.13 | 0 | 5 |
| **Distance band *i*=0-3 km** | | | | | |
| *Active* $_3$ | Number of active sites | 0.12 | 0.33 | 0 | 1 |
| *Historic* $_{31}$ | Number of historical sites closed *j*=1-10 years ago | 1.10 | 1.08 | 0 | 5 |
| *Historic* $_{32}$ | Number of historical sites closed *j*=11-20 years ago | 1.55 | 1.39 | 0 | 6 |
| *Historic* $_{33}$ | Number of historical sites closed *j*=over 20 years ago | 3.30 | 1.87 | 0 | 9 |
| *Historic* $_{34}$ | Number of historical sites closed *j*=on unknown dates | 2.68 | 1.48 | 0 | 8 |
| **Distance band *i*=0-4 km** | | | | | |
| *Active* $_4$ | Number of active sites | 0.30 | 0.48 | 0 | 3 |
| *Historic* $_{41}$ | Number of historical sites closed *j*=1-10 years ago | 2.04 | 1.66 | 0 | 14 |
| *Historic* $_{42}$ | Number of historical sites closed *j*=11-20 years ago | 2.75 | 1.90 | 0 | 9 |
| *Historic* $_{43}$ | Number of historical sites closed *j*=over 20 years ago | 5.48 | 2.55 | 0 | 14 |
| *Historic* $_{44}$ | Number of historical sites closed *j*=on unknown dates | 4.69 | 1.84 | 0 | 11 |

## Table 3.24: Estimation results of Model 3

**OLS**
**Total observation: 10,792 cross sections**
**Dependent variable: ln(property prices)**

| | 1 km | 2 km | 3 km | 4 km | Best |
|---|---|---|---|---|---|
| ***Structural Variables*** | | | | | |
| Floor Area | 0.0041*** | 0.0042*** | 0.0041*** | 0.0042*** | 0.0041*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Garden Area | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Sales Date | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Age | -0.0223*** | -0.0234*** | -0.0231*** | -0.0228*** | -0.0224*** |
| | (0.0035) | (0.0035) | (0.0035) | (0.0035) | (0.0035) |
| Beds | 0.0089* | 0.0080* | 0.0088* | 0.0083* | 0.0088* |
| | (0.0048) | (0.0048) | (0.0048) | (0.0048) | (0.0048) |
| WCs | 0.0107* | 0.0100* | 0.0113* | 0.0114** | 0.0107* |
| | (0.0058) | (0.0058) | (0.0058) | (0.0058) | (0.0058) |
| Floors | -0.1503*** | -0.1501*** | -0.1496*** | -0.1510*** | -0.1499*** |
| | (0.0120) | (0.0121) | (0.0121) | (0.0121) | (0.0120) |
| Garage | 0.0733*** | 0.0735*** | 0.0729*** | 0.0735*** | 0.0736*** |
| | (0.0061) | (0.0062) | (0.0062) | (0.0062) | (0.0061) |
| Detached | 0.0164 | 0.0181 | 0.0187 | 0.0183 | 0.0169 |
| Bungalow | (0.0245) | (0.0245) | (0.0246) | (0.0246) | (0.0245) |
| Semi-Detached | -0.0963*** | -0.0911*** | -0.0920*** | -0.0913*** | -0.0972*** |

| | | | | | |
|---|---|---|---|---|---|
| Bungalow | (0.0283) | (0.0284) | (0.0284) | (0.0284) | (0.0283) |
| End Terrace | -0.2468** | -0.2454** | -0.2478** | -0.2496** | -0.2468** |
| Bungalow | (0.1055) | (0.1056) | (0.1058) | (0.1059) | (0.1055) |
| Terrace | -0.0841 | -0.1062 | -0.1085 | -0.0975 | -0.0909 |
| Bungalow | (0.1355) | (0.1357) | (0.1359) | (0.1360) | (0.1355) |
| Detached House | 0.1289*** | 0.1306*** | 0.1285*** | 0.1289*** | 0.1286*** |
| | (0.0095) | (0.0095) | (0.0095) | (0.0095) | (0.0095) |
| End Terrace | -0.0846*** | -0.0869*** | -0.0869*** | -0.0867*** | -0.0847*** |
| House | (0.0084) | (0.0084) | (0.0084) | (0.0084) | (0.0084) |
| Terrace House | -0.0980*** | -0.0981*** | -0.0985*** | -0.0989*** | -0.0981*** |
| | (0.0074) | (0.0074) | (0.0074) | (0.0074) | (0.0074) |
| BG1 | -0.0509 | -0.0317 | -0.0486 | -0.0461 | -0.0488 |
| | (0.1172) | (0.1174) | (0.1176) | (0.1176) | (0.1172) |
| BG2 | 0.2363*** | 0.2413*** | 0.2392*** | 0.2358*** | 0.2367*** |
| | (0.0839) | (0.0840) | (0.0841) | (0.0842) | (0.0839) |
| BG3 | -0.0881*** | -0.0905*** | -0.0866*** | -0.0875*** | -0.0857*** |
| | (0.0189) | (0.0190) | (0.0190) | (0.0190) | (0.0189) |
| BG4 | -0.0260* | -0.0207 | -0.0237* | -0.0242* | -0.0248* |
| | (0.0140) | (0.0140) | (0.0140) | (0.0140) | (0.0140) |
| BG5 | 0.0581* | 0.0623* | 0.0564* | 0.0581* | 0.0599* |
| | (0.0329) | (0.0329) | (0.0330) | (0.0330) | (0.0329) |
| BG8 | 0.0725*** | 0.0822*** | 0.0768*** | 0.0767*** | 0.0747*** |
| | (0.0199) | (0.0200) | (0.0200) | (0.0200) | (0.0199) |
| BG9 | 0.0742*** | 0.0820*** | 0.0804*** | 0.0809*** | 0.0747*** |
| | (0.0282) | (0.0282) | (0.0283) | (0.0283) | (0.0282) |
| BG10 | -0.3294*** | -0.3348*** | -0.3236*** | -0.3286*** | -0.3291*** |
| | (0.0451) | (0.0451) | (0.0452) | (0.0452) | (0.0451) |
| BG19 | 0.1019*** | 0.1072*** | 0.1025*** | 0.1064*** | 0.1013*** |
| | (0.0235) | (0.0235) | (0.0236) | (0.0236) | (0.0235) |
| BG20 | -0.0983*** | -0.0943*** | -0.1012*** | -0.1008*** | -0.0986*** |
| | (0.0096) | (0.0096) | (0.0096) | (0.0096) | (0.0096) |
| BG24 | 0.1072*** | 0.1036*** | 0.1079*** | 0.1082*** | 0.1077*** |
| | (0.0212) | (0.0212) | (0.0212) | (0.0212) | (0.0212) |
| BG25 | -0.6639*** | -0.6524*** | -0.6500*** | -0.6551*** | -0.6607*** |
| | (0.1105) | (0.1106) | (0.1108) | (0.1109) | (0.1105) |
| BG30 | -0.1200*** | -0.1304*** | -0.1278*** | -0.1242*** | -0.1205*** |
| | (0.0139) | (0.0139) | (0.0139) | (0.0140) | (0.0139) |
| BG31 | -0.0533*** | -0.0582*** | -0.0559*** | -0.0550*** | -0.0528*** |
| | (0.0160) | (0.0160) | (0.0160) | (0.0160) | (0.0160) |
| BG32 | 0.0548** | 0.0557** | 0.0529** | 0.0561*** | 0.0540** |
| | (0.0216) | (0.0216) | (0.0217) | (0.0217) | (0.0216) |
| BG35 | 0.0294 | 0.0281 | 0.0370 | 0.0324 | 0.0274 |
| | (0.0684) | (0.0684) | (0.0686) | (0.0686) | (0.0683) |
| BG36 | -0.2444*** | -0.2427*** | -0.2347*** | -0.2281*** | -0.2414*** |
| | (0.0399) | (0.0400) | (0.0400) | (0.0401) | (0.0399) |
| ***Neighbourhood Variables*** | | | | | |
| Age60 | 0.0001 | 0.0005 | 0.0004 | 0.0005 | -0.0000 |

| | | | | | |
|---|---|---|---|---|---|
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Unemployment | -0.0088*** | -0.0089*** | -0.0088*** | -0.0087*** | -0.0088*** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| White | 0.0045*** | 0.0045*** | 0.0040*** | 0.0041*** | 0.0045*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Asian | 0.0054*** | 0.0051*** | 0.0052*** | 0.0052*** | 0.0055*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Family with | 0.0001 | 0.0003 | 0.0002 | 0.0002 | 0.0001 |
| children | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| ***Accessibility Variables*** | | | | | |
| Primary Schools | 0.1618*** | 0.1602*** | 0.1613*** | 0.1676*** | 0.1603*** |
| | (0.0173) | (0.0174) | (0.0174) | (0.0173) | (0.0173) |
| Shops | -0.0140*** | -0.0106*** | -0.0116*** | -0.0113*** | -0.0142*** |
| | (0.0033) | (0.0032) | (0.0032) | (0.0032) | (0.0033) |
| Rail Station | -0.0012*** | -0.0007*** | -0.0008*** | -0.0008*** | -0.0012*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Park | -0.0002 | 0.0000 | -0.0002 | -0.0000 | -0.0001 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| University | -0.0024*** | -0.0024*** | -0.0021*** | -0.0022*** | -0.0024*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| CBD | 0.0008 | 0.0018 | 0.0006 | 0.0010 | 0.0009 |
| | (0.0014) | (0.0014) | (0.0014) | (0.0014) | (0.0014) |
| Motorway | 0.0035*** | 0.0028** | 0.0029** | 0.0028** | 0.0032*** |
| Junction | (0.0011) | (0.0011) | (0.0011) | (0.0011) | (0.0011) |
| Airport | -0.0071*** | -0.0068*** | -0.0072*** | -0.0070*** | -0.0072*** |
| | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) |
| Mosque | 0.0358*** | 0.0281*** | 0.0300*** | 0.0306*** | 0.0355*** |
| | (0.0042) | (0.0043) | (0.0043) | (0.0043) | (0.0042) |
| Industry A | 0.0424*** | 0.0435*** | 0.0466*** | 0.0459*** | 0.0436*** |
| | (0.0045) | (0.0046) | (0.0047) | (0.0047) | (0.0045) |
| Industry B | -0.0049 | -0.0007 | 0.0004 | -0.0022 | -0.0040 |
| | (0.0069) | (0.0068) | (0.0068) | (0.0070) | (0.0069) |
| Motorway | 0.0052 | 0.0026 | 0.0088* | 0.0121** | 0.0032 |
| | (0.0047) | (0.0048) | (0.0050) | (0.0050) | (0.0047) |
| Road A | -0.0265*** | -0.0289*** | -0.0265*** | -0.0256*** | -0.0248*** |
| | (0.0081) | (0.0081) | (0.0082) | (0.0081) | (0.0081) |
| Road B | -0.0116* | -0.0051 | -0.0091 | -0.0062 | -0.0121* |
| | (0.0063) | (0.0064) | (0.0064) | (0.0064) | (0.0063) |
| Minor Road | -0.2609** | -0.2512* | -0.2712** | -0.2534* | -0.2641** |
| | (0.1324) | (0.1326) | (0.1328) | (0.1330) | (0.1324) |
| Railway | 0.0178** | 0.0138** | 0.0058 | 0.0075 | 0.0159** |
| | (0.0069) | (0.0069) | (0.0069) | (0.0070) | (0.0070) |
| ***Environmental Variables*** | | | | | |
| Water View | 0.0000 | 0.0001 | 0.0000 | 0.0000 | 0.0000 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Park View | -0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0000 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |

| | | | | | |
|---|---|---|---|---|---|
| Road View | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Rail View | -0.0018*** | -0.0019*** | -0.0019*** | -0.0018*** | -0.0019*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Road Noise | -0.0017*** | -0.0018*** | -0.0018*** | -0.0018*** | -0.0017*** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Rail Noise | -0.0029 | -0.0018 | -0.0023 | -0.0025 | -0.0028 |
| | (0.0019) | (0.0020) | (0.0020) | (0.0020) | (0.0019) |
| Airport Noise | 0.0011 | 0.0022 | 0.0032 | 0.0032 | 0.0011 |
| | (0.0026) | (0.0026) | (0.0026) | (0.0026) | (0.0026) |
| $NO_2$ | 0.0006*** | 0.0005*** | 0.0006*** | 0.0005*** | 0.0006*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| CO | 0.0089 | 0.0104 | 0.0095 | 0.0132* | 0.0085 |
| | (0.0067) | (0.0067) | (0.0067) | (0.0068) | (0.0067) |
| ***Ward*** | | | | | |
| Aston | -0.0841** | -0.1434*** | -0.0187 | -0.0361 | -0.0745** |
| | (0.0333) | (0.0345) | (0.0360) | (0.0351) | (0.0334) |
| Bartley Green | -0.0534 | -0.1008** | -0.0008 | -0.0059 | -0.0656 |
| | (0.0486) | (0.0497) | (0.0500) | (0.0492) | (0.0489) |
| Billesley | 0.0384 | 0.0125 | 0.0402 | 0.0480 | 0.0401 |
| | (0.0338) | (0.0334) | (0.0330) | (0.0339) | (0.0338) |
| Bournville | 0.0710* | 0.0380 | 0.1272*** | 0.1313*** | 0.0726* |
| | (0.0408) | (0.0410) | (0.0403) | (0.0407) | (0.0408) |
| Brandwood | 0.0738* | 0.0342 | 0.1089*** | 0.0873** | 0.0781* |
| | (0.0401) | (0.0401) | (0.0403) | (0.0405) | (0.0402) |
| Edgbaston | 0.1281*** | 0.0897** | 0.1814*** | 0.1785*** | 0.1208*** |
| | (0.0405) | (0.0410) | (0.0419) | (0.0420) | (0.0406) |
| Erdington | 0.1551*** | 0.1000*** | 0.1561*** | 0.1767*** | 0.1494*** |
| | (0.0282) | (0.0292) | (0.0304) | (0.0288) | (0.0283) |
| Fox Hollies | -0.0127 | -0.0272 | 0.0226 | 0.0180 | -0.0106 |
| | (0.0229) | (0.0224) | (0.0217) | (0.0221) | (0.0229) |
| Hall Green | 0.0130 | -0.0225 | 0.0278 | 0.0305 | 0.0152 |
| | (0.0259) | (0.0258) | (0.0256) | (0.0257) | (0.0259) |
| Handsworth | -0.0217 | -0.0447 | 0.0160 | 0.0192 | -0.0187 |
| | (0.0337) | (0.0350) | (0.0346) | (0.0357) | (0.0337) |
| Harborne | 0.1775*** | 0.1360*** | 0.2214*** | 0.2397*** | 0.1735*** |
| | (0.0459) | (0.0455) | (0.0445) | (0.0455) | (0.0459) |
| Hodge Hill | 0.1466*** | 0.1567*** | 0.1508*** | 0.1401*** | 0.1388*** |
| | (0.0277) | (0.0282) | (0.0286) | (0.0285) | (0.0279) |
| King's Norton | 0.0488 | 0.0077 | 0.1207** | 0.1279*** | 0.0475 |
| | (0.0482) | (0.0481) | (0.0485) | (0.0483) | (0.0482) |
| Kingsbury | 0.1825*** | 0.1268*** | 0.1670*** | 0.1905*** | 0.1786*** |
| | (0.0346) | (0.0352) | (0.0359) | (0.0355) | (0.0346) |
| Kingstanding | 0.1043*** | 0.0608* | 0.1084*** | 0.1283*** | 0.0979*** |
| | (0.0322) | (0.0334) | (0.0339) | (0.0342) | (0.0323) |
| Ladywood | 0.0286 | -0.0130 | 0.0619 | 0.0874** | 0.0192 |
| | (0.0384) | (0.0397) | (0.0414) | (0.0420) | (0.0386) |

| | | | | | |
|---|---|---|---|---|---|
| Longbridge | 0.1040** | 0.0540 | 0.1437*** | 0.1352*** | 0.1029** |
| | (0.0469) | (0.0475) | (0.0480) | (0.0480) | (0.0469) |
| Moseley | 0.1669*** | 0.1130*** | 0.1906*** | 0.1861*** | 0.1641*** |
| | (0.0368) | (0.0375) | (0.0371) | (0.0366) | (0.0368) |
| Nechells | 0.0829*** | 0.0198 | 0.1086*** | 0.0854*** | 0.0975*** |
| | (0.0311) | (0.0318) | (0.0317) | (0.0308) | (0.0317) |
| Northfield | 0.0198 | -0.0234 | 0.0786* | 0.0860* | 0.0161 |
| | (0.0454) | (0.0457) | (0.0460) | (0.0453) | (0.0454) |
| Oscott | 0.0370 | -0.0000 | 0.0082 | 0.0449 | 0.0263 |
| | (0.0339) | (0.0353) | (0.0356) | (0.0354) | (0.0342) |
| Perry Barr | -0.0011 | -0.0723** | -0.0450 | -0.0102 | -0.0076 |
| | (0.0345) | (0.0356) | (0.0354) | (0.0364) | (0.0346) |
| Quinton | 0.0371 | -0.0095 | 0.0786* | 0.0792* | 0.0244 |
| | (0.0472) | (0.0471) | (0.0468) | (0.0472) | (0.0475) |
| Sandwell | -0.0237 | -0.0821** | -0.0234 | 0.0077 | -0.0336 |
| | (0.0319) | (0.0334) | (0.0339) | (0.0345) | (0.0322) |
| Selly Oak | 0.1217*** | 0.0579 | 0.1536*** | 0.1512*** | 0.1209*** |
| | (0.0429) | (0.0428) | (0.0419) | (0.0420) | (0.0429) |
| Shard End | 0.0754** | 0.0572* | 0.0763** | 0.0873*** | 0.0677** |
| | (0.0317) | (0.0319) | (0.0323) | (0.0321) | (0.0318) |
| Sheldon | -0.0208 | -0.0692*** | -0.0070 | 0.0037 | -0.0147 |
| | (0.0246) | (0.0245) | (0.0234) | (0.0248) | (0.0248) |
| Small Heath | 0.0685*** | 0.0142 | 0.0309 | 0.0456** | 0.0678*** |
| | (0.0241) | (0.0242) | (0.0230) | (0.0229) | (0.0241) |
| Soho | -0.2084*** | -0.2752*** | -0.2112*** | -0.1808*** | -0.2209*** |
| | (0.0338) | (0.0351) | (0.0366) | (0.0372) | (0.0341) |
| Sparkbrook | -0.0249 | -0.0707** | -0.0429 | -0.0133 | -0.0342 |
| | (0.0335) | (0.0343) | (0.0336) | (0.0332) | (0.0337) |
| Sparkhill | 0.0750** | 0.0054 | 0.0539* | 0.0653** | 0.0708** |
| | (0.0304) | (0.0310) | (0.0301) | (0.0294) | (0.0304) |
| Stockland Green | 0.0665** | 0.0210 | 0.0928*** | 0.0959*** | 0.0692** |
| | (0.0305) | (0.0313) | (0.0318) | (0.0320) | (0.0305) |
| Sutton Four | 0.4985*** | 0.4579*** | 0.4890*** | 0.5196*** | 0.4998*** |
| Oaks | (0.0418) | (0.0419) | (0.0435) | (0.0455) | (0.0418) |
| Sutton New Hall | 0.4046*** | 0.3683*** | 0.4072*** | 0.4354*** | 0.4021*** |
| | (0.0311) | (0.0318) | (0.0345) | (0.0357) | (0.0311) |
| Sutton Vesey | 0.3034*** | 0.2564*** | 0.3069*** | 0.3298*** | 0.2974*** |
| | (0.0295) | (0.0300) | (0.0323) | (0.0323) | (0.0296) |
| Washwood | 0.0245 | 0.0006 | 0.0465* | 0.0317 | 0.0318 |
| Heath | (0.0270) | (0.0283) | (0.0281) | (0.0264) | (0.0272) |
| Weoley | -0.0508 | -0.1004** | -0.0005 | 0.0072 | -0.0548 |
| | (0.0443) | (0.0445) | (0.0441) | (0.0444) | (0.0443) |
| Yardley | 0.0337 | 0.0372* | 0.0777*** | 0.0646*** | 0.0309 |
| | (0.0220) | (0.0217) | (0.0223) | (0.0217) | (0.0220) |
| ***Landfill Variables*** | | | | | |
| *Active$_1$* | -0.0502 | | | | |
| | (0.0539) | | | | |

| | | | | | |
|---|---|---|---|---|---|
| *Historic₁₁* | -0.0277*** | | | | -0.0273*** |
| | (0.0077) | | | | (0.0077) |
| *Historic₁₂* | -0.0211*** | | | | -0.0221*** |
| | (0.0073) | | | | (0.0073) |
| *Historic₁₃* | -0.0364*** | | | | -0.0355*** |
| | (0.0047) | | | | (0.0047) |
| *Historic₁₄* | 0.0028 | | | | 0.0025 |
| | (0.0051) | | | | (0.0051) |
| *Active ₂* | | 0.0481*** | | | |
| | | (0.0183) | | | |
| *Historic ₂₁* | | 0.0004 | | | |
| | | (0.0049) | | | |
| *Historic ₂₂* | | -0.0328*** | | | |
| | | (0.0048) | | | |
| *Historic ₂₃* | | -0.0012 | | | |
| | | (0.0034) | | | |
| *Historic ₂₄* | | 0.0017 | | | |
| | | (0.0032) | | | |
| *Active ₃* | | | -0.0345*** | | -0.0286*** |
| | | | (0.0113) | | (0.0111) |
| *Historic ₃₁* | | | 0.0130*** | | |
| | | | (0.0042) | | |
| *Historic ₃₂* | | | -0.0104** | | |
| | | | (0.0042) | | |
| *Historic ₃₃* | | | 0.0083*** | | |
| | | | (0.0030) | | |
| *Historic ₃₄* | | | 0.0001 | | |
| | | | (0.0032) | | |
| *Active ₄* | | | | -0.0059 | |
| | | | | (0.0081) | |
| *Historic ₄₁* | | | | 0.0085*** | |
| | | | | (0.0028) | |
| *Historic ₄₂* | | | | -0.0017 | |
| | | | | (0.0034) | |
| *Historic ₄₃* | | | | 0.0069*** | |
| | | | | (0.0024) | |
| *Historic ₄₄* | | | | -0.0025 | |
| | | | | (0.0026) | |
| Constant | 10.5849*** | 10.5952*** | 10.5115*** | 10.4564*** | 10.6063*** |
| | (0.0921) | (0.0922) | (0.0927) | (0.0944) | (0.0925) |
| ***Diagnostic tests*** | | | | | |
| ***N*** | 10792 | 10792 | 10792 | 10792 | 10792 |
| $R^2$ | 0.7668 | 0.7663 | 0.7656 | 0.7653 | 0.7669 |
| Adjusted $R^2$ | 0.7645 | 0.7640 | 0.7633 | 0.7630 | 0.7646 |
| AIC | -752.0923 | -727.3822 | -695.1177 | -683.5342 | -757.9508 |
| Jarque-bera | 4877 | 4941 | 4963 | 5000*** | 4896*** |
| Multicollinearity | 0.23319117 | 0.23372572 | 0.23442552 | 0.23467728 | 0.23306462 |

| | | | | | |
|---|---|---|---|---|---|
| Breusch-Pagan | 0.11 | 0.59 | 0.09 | 0.23 | 0.10 |
| Ramsey RESET | 51.20*** | 53.65*** | 54.67*** | 52.62*** | 51.70*** |
| **F-test** | | | | | |
| All landfill bands | 17.06*** | 12.13*** | 5.72*** | 3.42*** | 18.23*** |
| Historical landfill bands | 21.30*** | 12.66*** | 5.12*** | 4.25*** | 20.75*** |
| Equality of coefficient sizes across all landfill bands | 7.28*** | 11.62*** | 6.27*** | 3.25** | 7.08*** |
| Equality of coefficient sizes across all historical bands | 9.67*** | 12.07*** | 5.63*** | 4.27*** | 9.06*** |

*Notes*: See notes for Table 3.20.

The coefficients on the landfill variables show a mixed set of results in terms of both statistical significance and signs across different distance bands. For instance, the number of active sites within 1 km of the property is not statistically significant but becomes significant within the 0-2 km and 0-3 km range. This would seem to be because there are too few observations of houses within 1 km of active sites as shown in Table 3.11. For example, only 20 out of 10,792 observations had an active site within 1 km.

However, most coefficients for historical sites of differing vintage within 1 km are significant at the 1% level and have a negative sign as expected. But some of these coefficients become statistically insignificant or positively signed as the distance band increases from 0-1 km to 0-2 km or 0-3 km.

F tests for joint significance are shown in the Table 3.24. These test statistics reject the null hypothesis that the coefficients on the landfill variables are jointly zero. F-test also rejects the hypothesis that the coefficients on the historical landfill variables are all jointly zero. Disamenity effects of landfills are jointly significant statistically regardless of their operating status and history. Further F-tests for the equality of coefficients across active and historical sites yield significant results indicating that landfill impacts vary between active and historical sites, and also across historical sites of different vintages.

The estimates of disamenity impacts are extremely sensitive to assumptions about what is the correct distance band. At the very least such findings suggest varying the spatial limits across landfill sites with different operating status. Active and historical landfill sites may have a different spatial externality field. In an attempt to identify the best distance bands for active and historical sites, all possible combinations of distance bands were estimated and then compared in terms of the goodness.

**Table 3.25: Best distance band for active and historical landfills**

| | Historic 0-1 | Historic 0-2 | Historic 0-3 | Historic 0-4 |
|---|---|---|---|---|
| **Active 0-1** | 0.764518 | 0.763837 | 0.763066 | 0.763005 |
| **Active 0-2** | 0.764596 | 0.763978 | 0.763316 | 0.763218 |
| **Active 0-3** | 0.764645 | 0.764036 | 0.763271 | 0.763178 |
| **Active 0-4** | 0.76451 | 0.763833 | 0.763066 | 0.763017 |

Table 3.25 shows the adjusted $R^2$ of each combination. The combination of the number of active sites within 3 km and the number of historical sites within 1 km produces the highest adjusted $R^2$.

The last column of Table 3.24 shows the regression results of this preferred combination. The adjusted $R^2$ is 0.7671. The coefficient estimates indicate that the disamenity impact is 2.6% per site within 3 km for active sites and the impact of historical sites within the 1 km range varies from 2.4% to 3.4% per site depending on the closing date. Given the average sales price in Birmingham, these impacts amount to £1,534 for an active site within 3 km and range from £1,416 to £2,006 for an historical site within 1 km from the property depending on the closing date. It is also apparent that almost all historical sites are statistically significant at the 1% level irrespective of their vintage except those sites with unknown closing dates. This implies that landfill disamenity impacts last for at least 20 years following site closure.

### 3.5.4 Spatial Hedonic Approach

So far, the estimation of the hedonic price functions is based on the assumption that individual property sales are spatially independent. However, the recognition that geographic data tend to spatially dependent or spatially heterogeneous has attracted a growing interest in spatial data analysis and modelling techniques. The presence of spatial dependence and its specification is of particular importance in hedonic analysis since property values and their attributes are spatial data. Increasingly therefore hedonic price studies have incorporated spatial analysis using various spatial econometric methods.

Early spatial hedonic studies (e.g. Dubin, 1988, 1992) specify neighbourhood effects using the geostatistical or the direct representation approach. Dubin (1988) specifies spatial autocorrelation in the variance-covariance matrix as a function of distance between observations. A review of this approach is provided in Dubin et al. (1999). Alternatively, other studies (e.g. Can, 1990, 1992; Pace and Gilley, 1997; Tsutsumi et al., 1999; Day, 2003; Tsutsumi and Seya, 2009) employ the spatial econometrics approach by systematically testing for spatial autocorrelation and modelling spatial dependence in the regression with spatially autoregressive terms. Their findings suggest the application of explicit spatial econometric methods improves the overall prediction of house prices. The first step of this approach involves the specification of the spatial weights matrix. Given an exogenous spatial weights matrix, house prices are generated by a spatial process either in the form of spatially lagged variables or in the error structure. In the house market, spatial lag models capture direct effects of the price of neighbourhood while spatial error models capture spatially correlated error terms. A review of spatial econometric theory and its applications in economics can be found in Anselin (1998) and Anselin et al. (2004).

In the context of environmental quality, studies like Kim et al. (2003) and Anselin and Lozano-Gracia (2008) use the spatial econometric approach for benefit evaluation of improved air quality in urban areas. For landfill disamenity, Brasington and Hite (2005) use the spatial Durbin model which includes a spatial lag of the dependent variable as well as spatial lags of the explanatory variables. They find strong evidence of spatial interaction in the form of statistically significant spatially lagged dependent variables. Wang (2006) argues that the spatial error component (SEC) model captures any house-specific error that arises from mis-measurement of house prices. Furthermore, row-standardizing the spatial weights matrix is considered of particular importance since it affects the scales of neighbouring influence through number and distance effects.[62]

In this section, I employ commonly used spatial econometric tools, chiefly the spatial lag and error model to specify any significant effect from spatial autocorrelation in house prices in Birmingham. In what follows a number of conceptual issues in spatial econometrics are reviewed namely the construction of spatial weights, spatial dependence tests and the specification of spatial interdependence in regression analysis.

#### 3.5.4.1 Spatial Weight Matrix

The construction of the spatial weights matrix ($W$) precedes estimating the spatial hedonic model. $W$ defines the structure or range of potential interaction of geographical units with

[62] Under row-standardisation, the sum of all elements in a row is one so that the number of neighbours does not matter in the sense that total amount of accepted influence is equal across all observations. Non-standardisation means that observations with a large number of neighbours will always get a high degree of neighbouring effects since the spatially lagged term will be greater with more neighbours. Wang (2006) labels it the "number effect" of row-standardisation. However, he argues that such an effect would be relevant to the spatially lagged house price in the lag model not the spatial error model. The spatially lagged error term in the error model should be treated as a signal for unobserved spatial variables rather than direct effects of neighbourhood. Thus, the greater the number of neighbours, the more information the spatial model can incorporate in its specification. All of these arguments show the importance of the way a spatial weights matrix is specified in the spatial analysis.

elements $w_{ij}$, where $ij$ index corresponds to each observation $i$ and $j$. Each element shows the strength of a bilateral tie based on the spatial relationship between two observations.[63]

In the current study, the spatial weights matrix is specified as a row-standardised inverse distance matrix. The inverse form is adopted to allow a decaying influence of neighbouring observations over distance. A critical distance value, $d$, is essential in the current study for computationally feasible and more efficient estimation of the large dataset of Birmingham.[64] Using $x$, $y$ coordinates of each house, the average distance of the nearest neighbours is calculated at 50.409 m and the maximum distance of the nearest is 589.99 m. Thus, the critical distance value, $d$, must be greater than 589.99 m in order to ensure that every observation has at least one neighbour. For $d$ set at 600 m as a conservative range of neighbourhood effects, the spatial weight matrix, $W$ takes the following form:

$$\begin{cases} w_{ij}^{*} = 0 & \text{if } \ i = j \\ w_{ij}^{*} = \dfrac{1}{d_{ij}} & \text{if } \ d_{ij} \le 600\,m \ \text{ and } \ w_{ij} = \dfrac{w_{ij}^{*}}{\sum_j w_{ij}^{*}} \\ w_{ij}^{*} = 0 & \text{if } \ d_{ij} > 600\,m \end{cases} \qquad \textbf{(3.15)}$$

where $w_{ij}$ is a row-standardised element of the spatial weights matrix. Table 3.26 summarises the characteristics of the spatial weights matrix constructed.

[63] This can be represented by either geographical contiguity or distance. However, the distance-based weights matrix has been preferred since a contiguity matrix omits unconnected observations (Ertur and Le Gallo, 2003). The most commonly used distance-based weights matrices are: a binary weights matrix based on a critical distance cut-off, K nearest neighbours weights and inverse distance weights matrix. A critical distance cut-off can also be imposed to the latter two weights matrices to place a spatial limit of influence.

[64] A host of spatial econometric estimations are available in the Spatial Econometrics Toolbox for Matlab designed by James LeSage (http://www.spatial-econometrics.com). The estimation of large scale problems is solved using the sparse matrix functionality of Matlab.

**Table 3.26: The Summary of the spatial weights matrix**

| **Inverse distance with a cut off distance of 600m** | |
|---|---|
| Number of Features | 10,792 |
| Percentage of Spatial Connectivity | 0.62 |
| Average Number of Neighbours | 67.16 |
| Minimum Number of Neighbours | 1 |
| Maximum Number of Neighbours | 179 |

### 3.5.4.2 Spatial Autocorrelation

Spatial autocorrelation occurs when observations that are closely located are more related than those that are far away. There is a wide range of statistics available to test whether observations are clustered, dispersed or randomly distributed in terms of a particular feature.[65] Of these, Moran's *I* statistic is the best known measurement of global spatial autocorrelation. The formula for deriving Moran's *I* (Moran, 1950) is given by:

$$I = \frac{n}{S_0} \cdot \frac{\sum_i \sum_j w_{ij} \cdot (x_i - \mu) \cdot (x_j - \mu)}{\sum_i (x_i - \mu)^2} \qquad \textbf{(3.16)}$$

where $n$ is the number of observations, $x_i$ and $x_j$ are observations for location $i$ and $j$, $w_{ij}$ is the corresponding element in the spatial weights matrix, *W*, and $\mu$ is the mean of the observations. $S_0$ is the sum of the elements of the weights matrix, which equals $n$ for a row-standardised spatial weights matrix. For statistical inference, a standardised *z*-score is constructed, based on the theoretical mean and standard deviation.[66] The interpretation is as follows. A statistically significant and positive *z*-score for Moran's *I* indicates high clustering among similar values, either high values or low values. On the other hand, a statistically

[65] See Anselin and Rey (2010) for various tests for spatial autocorrelation.

[66] For Moran's *I*, $z_I = I - E(I)/\sigma(I)$ where is $E(I) = -1/(n-1)$.

significant and negative $z$-score indicates negative spatial autocorrelation, such as regions with low values having neighbours with high values.

Similarly, the Getis-Ord General $G$ analysis produces a statistic for global spatial autocorrelation, defined as (Getis and Ord, 1992):

$$G = \frac{\sum_i \sum_j w_{ij} \cdot x_i x_j}{\sum_i \sum_j x_i x_j} \qquad \textbf{(3.17)}$$

where $w_{ij}$ must be an element of the symmetric and unstandardised spatial weights matrix. If the null hypothesis of no spatial clustering is rejected, then the sign of the $z$-score[67] becomes important. A statistically significant and positive $z$-score of the General $G$ indicates high values for the attribute are clustered in the study area. On the other hand, a statistically significant and negative $z$-score value indicates that low values are clustered in the study area.

**Table 3.27: Spatial statistics**

| | | Unstandardised | Row-standardised |
|---|---|---|---|
| **Spatial Autocorrelation** | Moran's Index | 0.576657 | 0.639877 |
| | Expected Index | -0.000093 | -0.000093 |
| | Variance | 0.000077 | 0.000014 |
| | $z$-score | 65.793897 | 173.457941 |
| | p-value | 0.000000 | 0.000000 |
| **High/Low Clustering** | Observed General G | 0.000029 | |
| | Expected General G | 0.000029 | |
| | Variance | 0.000000 | |
| | $z$-score | -18.355208 | |
| | p-value | 0.000000 | |

In order to detect spatial patterns in house prices across the city of Birmingham, the Moran's $I$ and General $G$ are calculated using the inverse distance weights matrix with a 600 m limit.[68]

[67] For General $G$, $z_G = G - E(G)/\sigma(G)$ where $E(G) = \sum_i \sum_j w_{ij} / n(n-1)$.

[68] The results do not change with different distance cut-off values. That is, Moran's $I$ and General $G$ statistics for

Table 3.27 displays the results of these tests for the natural log of house price. The results of Moran's $I$ for both the unstandardised and row-standardised spatial weights indicate a high degree of global clustering. The negative and significant $z$-score of General $G$ indicates a general tendency of low-value clustering.

In addition to a general tendency for the entire data set, the local structure of spatial autocorrelation is analysed using the local Moran's $I$. The local version of Moran's $I$ statistic assesses whether there are local spatial clusters or dispersion by comparing the values of each specific location with values in the neighbouring locations (Anselin, 1995). [69] The global Moran's $I$ statistic is proportional to the sum of local Moran's $I$ statistics for individual observations and thus the interpretations of signs for local statistics are the same as the preceding ones.

Figure 3.12 displays the results of local Moran's $I$ statistics on the map, using the same spatial weights matrix. On the map to the right, the observations are displayed according to p-values of statistics. Statistically insignificant observations in green and light green on this map reflect random distribution. On the other hand, those in red and yellow show the statistically significant pattern of either clustering or dispersion. The exact patterns of spatial distribution can be further examined on the map to the left.

As can be seen on the map to the left, the $z$-scores of those significant ones are positively signed and thus confirm the result of global Moran's $I$ statistic, which implies spatial clustering of like values, either low or high. The observations with negative z-score are outliers indicating the lack of clustering. That is, high (low) house prices are surrounded primarily by low (high) prices. However, the same observations are shown as green on the

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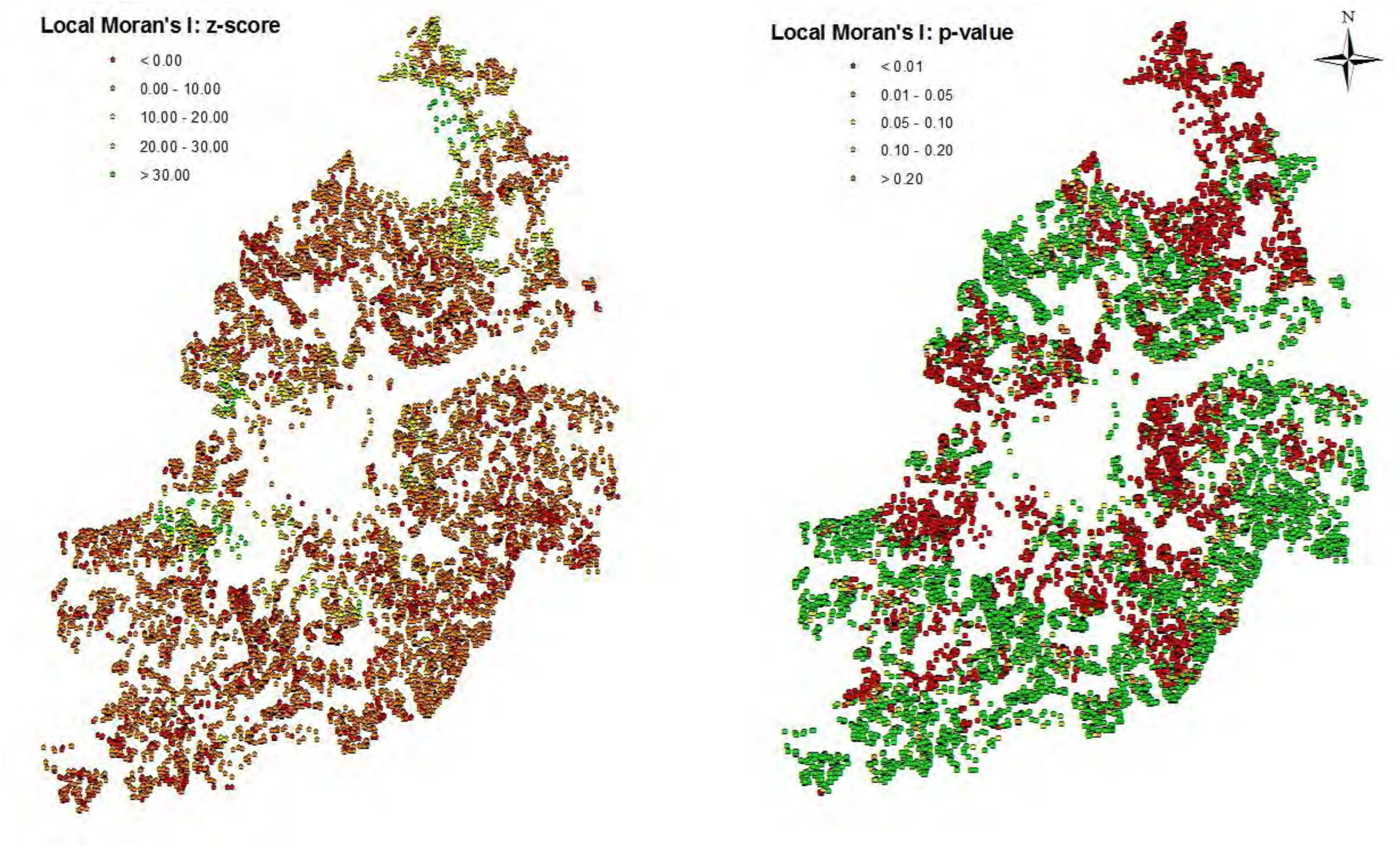
the other inverse distance weights matrices created with 700 m, 800 m, 900 m and 1000 m as a distance cut-off are all statistically significant at the 1% level.

[69] See Appendix 3.7 for the computation of local Moran's $I$.

**Figure 3.12: Clusters and outliers (Anselin Local Moran's *I*)**



right hand map indicating statistical insignificance. Overall, the spatial pattern of house prices in Birmingham highlights the importance of spatial interactions and geographical location.

#### 3.5.4.3 Spatial Regressions

Given the statistically significant presence of spatial autocorrelation in house prices, it may be taken into account in the specification of the regression using two common spatial models: the spatial error and lag model. The spatial error model is:

$$\ln(P) = \alpha + \beta X + u \quad \text{where} \quad u = \lambda W u + \varepsilon \qquad \textbf{(3.18)}$$

$X$ is a matrix of explanatory variables including landfill variables, $\beta$ is a vector of parameters to be estimated, $u$ is a vector of errors, $Wu$ is the spatial lag for the errors, $\lambda$ is the spatial autoregressive parameter and ε is a vector of independent and identically distributed errors. The autoregressive error term can be rewritten as $u = (I - \lambda W)^{-1} \cdot \varepsilon$ where $(I-\lambda W)^{-1}$ is the spatial multiplier which ensures a shock at location $i$ to be transferred across neighbours (Anselin, 2002). However, the marginal implicit price for housing characteristics can be calculated in the same way as with the non-spatial model. That is, for a unit change in the $m^{th}$ explanatory variable, the implicit price is $\beta_m P$ at the house price, $P$.

Alternatively a hedonic spatial lag model includes the spatially lagged house price, $W \cdot \ln(P)$ as one of the explanatory variables:

$$\ln(P) = \alpha + \rho \cdot W \ln(P) + \beta X + \varepsilon \qquad \textbf{(3.19)}$$

where $\rho$ is a spatial autocorrelation coefficient. The reduced form is:

$$\ln(P) = (I - \rho W)^{-1}(\alpha + \beta X) + (I - \rho W)^{-1}\varepsilon \qquad \textbf{(3.20)}$$

where $(I- \rho W)^{-1}$ is the spatial multiplier. This expression shows that the house price of a given location is not only affected by its own characteristics and errors but also by those of all other houses through the spatial multiplier.[70]

Unlike with the spatial error model the implicit price for a unit change in the $m^{th}$ explanatory variable id calculated as follows:

$$\frac{\partial P}{\partial X_m} = \beta_m P \cdot (1 - \rho W)^{-1} \qquad \textbf{(3.21)}$$

In the spatial error model, the correlated error terms across space lead to inefficient estimates of coefficients from OLS regression. In the spatial lag model, the dependent variable is directly related to its value in surrounding locations, which results in endogeneity, and thus coefficients from OLS regression are both biased and inefficient. Therefore, the estimation of spatial models is commonly carried out by means of ML or GMM.

Table 3.28 and 3.29 report the results of spatial error and lag versions of Models 1, 2 and the best specification of Model 3 (i.e. the number of active sites within 3 km and the number of historical sites within 1 km) obtained from ML estimation under the assumption of normally distributed error terms; $\varepsilon \sim N(0, \sigma^2 I)$.[71] The spatial weights matrix chosen is the inverse distance matrix with a 600 m limit.[72]

For Models 1 and 2, only the primary specifications are estimated, excluding dummies for site-specific characteristics. Overall, the inclusion of spatial dependence improves the

[70] This can be seen by decomposing the spatial multiplier using the formula for a sum to infinity:

$$\frac{\partial P}{\partial X_m} = \beta_m P(I + \rho W + \rho^2 W^2 + \rho^3 W^3 + \ldots) = P(I\beta_m + \rho W \beta_m + \rho^2 W^2 \beta_m + \rho^3 W^3 \beta_m \ \ldots)$$

The first term, $I\beta_m$, is the direct effect of $X_m$ on house prices. The second term, $\rho W\beta_m$, is indirect effects as it represents the effects of $X_m$ observed in neighbouring houses defined by the spatial weights matrix, $W$. Such indirect effects are referred to as spillovers from neighbours. The rest of the terms are referred to as induced effects as they show spillovers from higher-order neighbours (i.e. neighbours of neighbours). Therefore, the spatial lag model conceptualises global spatial effects by exploiting the links across all observations (Abreu at el., 2005, p.32).

[71] The results from GMM estimates, however, are similar in signs and statistical significance with the results from ML.

[72] The use of inverse distance weights matrix with a 700 m limit did not change the regression results.

explanatory power of the hedonic regressions, particularly employing the spatial error model. This is consistent with Bell and Bockstael (2000) who argue that spatial dependence in house prices is more likely to arise due to omitted information on the house and its neighbourhood or errors in measurement, rather than through the direct influence of price decisions in surrounding areas.

The statistical significance and signs of most variables in the spatial models generally follow the results of non-spatial models. However, some of landfill variables become insignificant. In both the spatial error and lag model, the difference between historical and active sites becomes statistically insignificant in Model 2. However, the disamenity from historical sites is still highly significant and its magnitude increased in the spatial error model and much smaller in the spatial lag model (although note that the coefficients of the spatial lag model are not directly comparable).

In Model 3, the number of active sites within 3 km turns out to be statistically insignificant in both the spatial error and lag model but again, historical sites still show strong negative effects on house prices. This may imply a need to identify a new spatial limit for active sites with the inclusion of spatial autocorrelation. Although the results of Model 2 and 3 are not as robust in terms of landfill variables, spatial effects in both forms are detected as a statistically significant factor in the hedonic regression. The spatial autoregressive parameters in the error and lag model are both statistically significant. In particular a positive sign on the spatial parameter of the lag model implies that the value of a property goes up with any increase in house prices in the surrounding area.

**Table 3.28: Estimation results of spatial error model**

| | | | |
|---|---|---|---|
| **ML** | | | |
| **Total observation: 10792 cross sections** | | | |
| **Dependent variable: ln(price)** | | | |
| | Model 1 | Model 2 | Model 3 |
| ***Structural Variables*** | | | |
| Floor area | 0.0036*** | 0.0036*** | 0.0033*** |
| Garden area | 0.0003*** | 0.0003*** | 0.0003*** |
| Sales Date | 0.0002*** | 0.0002*** | 0.0002*** |
| Age | -0.0186*** | -0.0182*** | -0.0200*** |
| Beds | 0.0119** | 0.0119** | 0.0081** |
| WCs | 0.0064 | 0.0061 | 0.0065 |
| Floors | -0.1461*** | -0.1455*** | -0.1295*** |
| Garage | 0.0686*** | 0.0688*** | 0.0627*** |
| Detached Bungalow | 0.0069 | 0.0061 | -0.0071 |
| Semi-Detached Bungalow | -0.1267*** | -0.1255*** | -0.1082*** |
| End Terrace Bungalow | -0.2451** | -0.2423** | -0.2238** |
| Terrace Bungalow | -0.0828 | -0.0798 | -0.0803 |
| Detached House | 0.1218*** | 0.1222*** | 0.1119*** |
| End Terrace House | -0.0817*** | -0.0819*** | -0.0689*** |
| Terrace House | -0.0939*** | -0.0944*** | -0.0838*** |
| BG1 | -0.1229 | -0.1168 | -0.0552 |
| BG2 | 0.2384*** | 0.2382*** | 0.2005*** |
| BG3 | -0.1051*** | -0.1075*** | -0.0528*** |
| BG4 | -0.0352** | -0.0365** | -0.0039** |
| BG5 | 0.0324 | 0.0322 | 0.0537 |
| BG8 | 0.0313 | 0.0321 | 0.0602 |
| BG9 | 0.0800*** | 0.0780*** | 0.0796*** |
| BG10 | -0.2510*** | -0.2550*** | -0.2734*** |
| BG19 | 0.0980*** | 0.0976*** | 0.0910*** |
| BG20 | -0.0750*** | -0.0743*** | -0.0611*** |
| BG24 | 0.1138*** | 0.1150*** | 0.0959*** |
| BG25 | -0.5348*** | -0.5383*** | -0.4252*** |
| BG30 | -0.1123*** | -0.1116*** | -0.0970*** |
| BG31 | -0.0538*** | -0.0520*** | -0.0548*** |
| BG32 | 0.0585*** | 0.0598*** | 0.0250*** |
| BG35 | 0.1067 | 0.1055 | -0.0419 |
| BG36 | -0.2220*** | -0.2259*** | -0.2168*** |
| ***Neighbourhood Variables*** | | | |
| Age60 | 0.0002 | 0.0002 | -0.0005 |
| Unemployment | -0.0085*** | -0.0086*** | -0.0062*** |
| White | 0.0016** | 0.0021*** | 0.0019*** |
| Asian | 0.0031*** | 0.0034*** | 0.0029*** |
| Family with children | -0.0002 | -0.0002 | -0.0007 |
| ***Accessibility Variables*** | | | |
| Primary Schools | 0.1352*** | 0.1313*** | 0.0704*** |

| | | | |
|---|---|---|---|
| Shops | -0.0176*** | -0.0191*** | 0.0001*** |
| Rail Station | -0.0012*** | -0.0012*** | -0.0005*** |
| Park | 0.0005 | 0.0005 | -0.0001 |
| University | -0.0027*** | -0.0028*** | -0.0013*** |
| CBD | 0.0020 | 0.0023 | 0.0016 |
| Motorway Junction | 0.0029* | 0.0027 | 0.0000* |
| Airport | -0.0074*** | -0.0068*** | -0.0036*** |
| Mosque | 0.0361*** | 0.0352*** | 0.0173*** |
| Industry A | 0.0443*** | 0.0408*** | 0.0209*** |
| Industry B | 0.0127 | 0.0085 | -0.0102 |
| Motorway | 0.0033 | 0.0091 | 0.0050 |
| Road A | -0.0348*** | -0.0368*** | -0.0163*** |
| Road B | -0.0101 | -0.0124 | -0.0004 |
| Minor Road | -0.3017* | -0.3006* | -0.5018* |
| Railway | 0.0085 | 0.0149 | 0.0166 |
| ***Environmental Variables*** | | | |
| Water View | 0.0005 | 0.0005 | 0.0001 |
| Park View | 0.0000 | 0.0000 | 0.0000 |
| Road View | 0.0002 | 0.0002 | 0.0002 |
| Rail View | -0.0014* | -0.0013* | -0.0013* |
| Road Noise | -0.0013** | -0.0012* | -0.0012** |
| Rail Noise | -0.0039* | -0.0039* | -0.0024** |
| Airport Noise | -0.0002 | 0.0015 | 0.0015 |
| $NO_2$ | 0.0002 | 0.0002 | 0.0004 |
| CO | 0.0003 | 0.0007 | 0.0084 |
| ***Ward*** | | | |
| Aston | -0.0324 | -0.0685 | -0.0281 |
| Bartley Green | -0.1119 | -0.0845 | -0.0509 |
| Billesley | 0.0201 | 0.0003 | 0.0085 |
| Bournville | 0.0215 | 0.0379 | 0.0330 |
| Brandwood | 0.0119 | 0.0182 | 0.0108 |
| Edgbaston | 0.1227** | 0.0953 | -0.0150* |
| Erdington | 0.1909*** | 0.2007*** | 0.0590*** |
| Fox Hollies | -0.0008 | -0.0337 | 0.0099 |
| Hall Green | 0.0325 | 0.0002 | -0.0139 |
| Handsworth | -0.0034 | -0.0281 | -0.0264 |
| Harborne | 0.0891 | 0.0977 | 0.0677 |
| Hodge Hill | 0.1483*** | 0.1616*** | 0.0591*** |
| King's Norton | -0.0115 | -0.0042 | -0.0175 |
| Kingsbury | 0.1657*** | 0.1762*** | 0.0793*** |
| Kingstanding | 0.1254** | 0.1368*** | 0.0387*** |
| Ladywood | -0.0139 | -0.0284 | -0.0201 |
| Longbridge | 0.0620 | 0.0439 | 0.0467 |
| Moseley | 0.1552*** | 0.1403*** | 0.0544*** |
| Nechells | 0.1060** | 0.0844* | 0.0862** |
| Northfield | 0.0110 | 0.0117 | -0.0094 |
| Oscott | 0.0754 | 0.0940* | 0.0248* |

| | | | |
|---|---|---|---|
| Perry Barr | -0.0176 | -0.0012 | -0.0068 |
| Quinton | -0.0010 | 0.0136 | -0.0246 |
| Sandwell | -0.0190 | -0.0148 | -0.0576* |
| Selly Oak | 0.0686 | 0.0747 | 0.0628 |
| Shard End | 0.0727 | 0.0907* | 0.0488* |
| Sheldon | 0.0249 | 0.0158 | -0.0046 |
| Small Heath | 0.0507 | 0.0486 | 0.0551* |
| Soho | -0.2233*** | -0.2136*** | -0.1138*** |
| Sparkbrook | -0.0216 | -0.0387 | -0.0106 |
| Sparkhill | 0.0678 | 0.0635 | 0.0164* |
| Stockland Green | 0.1387*** | 0.1381*** | 0.0212*** |
| Sutton Four Oaks | 0.5821*** | 0.5830*** | 0.1952*** |
| Sutton New Hall | 0.4508*** | 0.4574*** | 0.1748*** |
| Sutton Vesey | 0.3326*** | 0.3526*** | 0.1098*** |
| Washwood Heath | 0.0396 | 0.0215 | 0.0440 |
| Weoley | -0.0797 | -0.0641 | -0.0319 |
| Yardley | 0.0456 | 0.0411 | 0.0103 |
| ***Landfill Variables*** | | | |
| *Dist* | 0.0147** | 0.0396*** | |
| Active· *Dist* | | 0.0199 | |
| $Active_3$ | | | -0.0145 |
| $Historic_{11}$ | | | -0.0193** |
| $Historic_{12}$ | | | -0.0114 |
| $Historic_{13}$ | | | -0.0169*** |
| $Historic_{14}$ | | | 0.0024 |
| Constant | 10.8791*** | 10.8489*** | 5.8953*** |
| $\lambda$ | 0.5590*** | 0.5530*** | 0.4506*** |
| | | | |
| Adjusted $R^2$ | 0.7918 | 0.7918 | 0.7919 |
| Log-likelihood | 4735.8349 | 4740.5743 | 4746.4242 |

*Note*: Semi-detached houses, BG21 (Standard houses 1919-45), proportion of black residents and houses located in Acock's Green are omitted as baseline.

**Table 3.29: Estimation results of spatial lag model**

| **ML**<br>**Total observation: 10792 cross sections**<br>**Dependent variable: ln(price)** | | | |
|---|---|---|---|
| | Model 1 | Model 2 | Model 3 |
| ***Structural Variables*** | | | |
| Floor area | 0.0033*** | 0.0033*** | 0.0033*** |
| Garden area | 0.0003*** | 0.0003*** | 0.0003*** |
| Sales Date | 0.0002*** | 0.0002*** | 0.0002*** |
| Age | -0.0205*** | -0.0201*** | -0.0200*** |
| Beds | 0.0081* | 0.0081* | 0.0081* |

| | | | |
|---|---|---|---|
| WCs | 0.0068 | 0.0065 | 0.0065 |
| Floors | -0.1293*** | -0.1296*** | -0.1295*** |
| Garage | 0.0623*** | 0.0625*** | 0.0627*** |
| Detached Bungalow | -0.0066 | -0.0077 | -0.0072 |
| Semi-Detached Bungalow | -0.1060*** | -0.1058*** | -0.1082*** |
| End Terrace Bungalow | -0.2230** | -0.2217** | -0.2238** |
| Terrace Bungalow | -0.0833 | -0.0801 | -0.0803 |
| Detached House | 0.1114*** | 0.1120*** | 0.1118*** |
| End Terrace House | -0.0699*** | -0.0701*** | -0.0689*** |
| Terrace House | -0.0838*** | -0.0844*** | -0.0837*** |
| BG1 | -0.0532 | -0.0501 | -0.0552 |
| BG2 | 0.2001** | 0.2007** | 0.2004** |
| BG3 | -0.0515*** | -0.0537*** | -0.0527*** |
| BG4 | -0.0024 | -0.0034 | -0.0038 |
| BG5 | 0.0531* | 0.0533* | 0.0537* |
| BG8 | 0.0591*** | 0.0611*** | 0.0601*** |
| BG9 | 0.0831*** | 0.0815*** | 0.0796*** |
| BG10 | -0.2723*** | -0.2750*** | -0.2732*** |
| BG19 | 0.0918*** | 0.0929*** | 0.0909*** |
| BG20 | -0.0618*** | -0.0611*** | -0.0610*** |
| BG24 | 0.0938*** | 0.0955*** | 0.0958*** |
| BG25 | -0.4159*** | -0.4199*** | -0.4245*** |
| BG30 | -0.0992*** | -0.0984*** | -0.0969*** |
| BG31 | -0.0573*** | -0.0560*** | -0.0548*** |
| BG32 | 0.0236 | 0.0249 | 0.0249 |
| BG35 | -0.0436 | -0.0424 | -0.0421 |
| BG36 | -0.2124*** | -0.2167*** | -0.2167*** |
| ***Neighbourhood Variables*** | | | |
| Age60 | -0.0003 | -0.0003 | -0.0005 |
| Unemployment | -0.0061*** | -0.0062*** | -0.0062*** |
| White | 0.0016*** | 0.0019*** | 0.0019*** |
| Asian | 0.0027*** | 0.0030*** | 0.0029*** |
| Family with children | -0.0007 | -0.0007 | -0.0007 |
| ***Accessibility Variables*** | | | |
| Primary Schools | 0.0744*** | 0.0712*** | 0.0701*** |
| Shops | 0.0021 | 0.0008 | 0.0002 |
| Rail Station | -0.0003 | -0.0004 | -0.0005* |
| Park | 0.0000 | 0.0000 | -0.0001 |
| University | -0.0012*** | -0.0012*** | -0.0013*** |
| CBD | 0.0015 | 0.0016 | 0.0016 |
| Motorway Junction | -0.0002 | -0.0002 | 0.0000 |
| Airport | -0.0036*** | -0.0033*** | -0.0036*** |
| Mosque | 0.0163*** | 0.0155*** | 0.0173*** |
| Industry A | 0.0227*** | 0.0207*** | 0.0209*** |
| Industry B | -0.0098 | -0.0105* | -0.0102 |
| Motorway | 0.0056 | 0.0082* | 0.0050 |
| Road A | -0.0145* | -0.0163** | -0.0162** |

| | | | |
|---|---|---|---|
| Road B | 0.0021 | 0.0010 | -0.0004 |
| Minor Road | -0.5122*** | -0.5024*** | -0.5026*** |
| Railway | 0.0126* | 0.0146** | 0.0166** |
| ***Environmental Variables*** | | | |
| Water View | 0.0001 | 0.0001 | 0.0001 |
| Park View | 0.0000 | 0.0000 | 0.0000 |
| Road View | 0.0002 | 0.0002 | 0.0002 |
| Rail View | -0.0013** | -0.0013** | -0.0013* |
| Road Noise | -0.0013** | -0.0012** | -0.0012** |
| Rail Noise | -0.0020 | -0.0020 | -0.0024 |
| Airport Noise | 0.0016 | 0.0023 | 0.0015 |
| $NO_2$ | 0.0003** | 0.0004** | 0.0004** |
| CO | 0.0094 | 0.0099 | 0.0084 |
| ***Ward*** | | | |
| Aston | -0.0206 | -0.0406 | -0.0279 |
| Bartley Green | -0.0532 | -0.0397 | -0.0508 |
| Billesley | 0.0157 | 0.0065 | 0.0084 |
| Bournville | 0.0359 | 0.0414 | 0.0329 |
| Brandwood | 0.0036 | 0.0031 | 0.0106 |
| Edgbaston | -0.0035 | -0.0161 | -0.0154 |
| Erdington | 0.0552** | 0.0602** | 0.0587** |
| Fox Hollies | 0.0222 | 0.0051 | 0.0100 |
| Hall Green | -0.0077 | -0.0217 | -0.0140 |
| Handsworth | -0.0222 | -0.0264 | -0.0264 |
| Harborne | 0.0690* | 0.0728* | 0.0673 |
| Hodge Hill | 0.0504* | 0.0572** | 0.0589** |
| King's Norton | -0.0151 | -0.0125 | -0.0177 |
| Kingsbury | 0.0677** | 0.0738** | 0.0790** |
| Kingstanding | 0.0337 | 0.0401 | 0.0385 |
| Ladywood | -0.0123 | -0.0132 | -0.0202 |
| Longbridge | 0.0635 | 0.0523 | 0.0465 |
| Moseley | 0.0521 | 0.0475 | 0.0541 |
| Nechells | 0.0865*** | 0.0763*** | 0.0862*** |
| Northfield | -0.0042 | -0.0051 | -0.0095 |
| Oscott | 0.0090 | 0.0197 | 0.0248 |
| Perry Barr | -0.0308 | -0.0225 | -0.0068 |
| Quinton | -0.0245 | -0.0172 | -0.0248 |
| Sandwell | -0.0563** | -0.0488* | -0.0577** |
| Selly Oak | 0.0534 | 0.0550 | 0.0627 |
| Shard End | 0.0354 | 0.0465 | 0.0488 |
| Sheldon | -0.0071 | -0.0108 | -0.0046 |
| Small Heath | 0.0403* | 0.0440** | 0.0551** |
| Soho | -0.1202*** | -0.1098*** | -0.1135*** |
| Sparkbrook | -0.0100 | -0.0107 | -0.0105 |
| Sparkhill | 0.0019 | 0.0084 | 0.0163 |
| Stockland Green | 0.0186 | 0.0181 | 0.0211 |
| Sutton Four Oaks | 0.1731*** | 0.1764*** | 0.1942*** |

| | | | |
|---|---|---|---|
| Sutton New Hall | 0.1581*** | 0.1649*** | 0.1741*** |
| Sutton Vesey | 0.0908*** | 0.1038*** | 0.1092*** |
| Washwood Heath | 0.0428* | 0.0313 | 0.0440* |
| Weoley | -0.0310 | -0.0244 | -0.0318 |
| Yardley | 0.0123 | 0.0109 | 0.0102 |
| ***Landfill Variables*** | | | |
| *Dist* | 0.0065 | 0.0145*** | |
| Active· *Dist* | | 0.0305 | |
| $Active_3$ | | | -0.0144 |
| $Historic_{11}$ | | | -0.0193*** |
| $Historic_{12}$ | | | -0.0114* |
| $Historic_{13}$ | | | -0.0168*** |
| $Historic_{14}$ | | | 0.0024 |
| Constant | 5.7269*** | 5.7625*** | 5.8805*** |
| $\rho$ | 0.4630*** | 0.4570*** | 0.4520*** |
| Adjusted $R^2$ | 0.7697 | 0.7703 | 0.7712 |
| Log-likelihood | 4796.9372 | 4800.9623 | 4809.8005 |

*Notes*: See notes for Table 3.28.

### 3.5.5 Market Segmentation

Under the assumption of a single unified market, the analysis treats the area across the City of Birmingham as sufficiently homogeneous to be aggregated into a single hedonic pricing model. The coefficients of various attributes are held constant across the study area. However, as Straszheim (1974) notes, an urban area is likely to consist of a series of separate market and thus the assumption of a unique set of coefficients across all observations might not be valid.

Most existing hedonic studies deal with the problem of heterogeneous housing markets by subdividing the market into homogeneous subsets and estimating separate hedonic price functions for each subset. The criteria  commonly used for market segmentation is certain legal/political boundaries, property types or socio-economic characteristics of households while studies like Michael and Smith (1990) adopt the opinions of real estate agencies. Instead of a priori assumption, more recent hedonic studies (e.g. Day, 2003; Bateman et al.,

2004) attempt to identify the dominant characteristics which distinguish each cluster of properties via cluster analysis.

While most of studies use a representative characteristic to partition properties into a smaller number of submarkets, some studies (e.g. Kestens et al., 2006; Borst and McCluskey, 2008; Bitter et al., 2006) use property-specific characteristics as the building block for the segmentation by employing locally linear spatial models such as the spatial expansion model (Casetti, 1972) or geographically weighted regression (GWR). These models produce spatially varying parameters through the inclusion of locational information. According to Bitter et al. (2006, p.3), this approach has advantages over the submarket approach as it allows prices to vary in a continuous manner over space while the submarket approach views spatial heterogeneity as a discrete phenomenon: something which is often difficult to implement empirically.

In this study, we start by simply dividing observations according to property construction type between two groups; 1) semi-detached and detached houses/bungalows and 2) terrace and end terrace houses/bungalows. Table 3.30 reports estimation results with the entire dataset together and two sets of divided data. The best specification of Model 3 (i.e. the number of active sites within 3 km and the number of historical sites within 1 km for landfill variables) is chosen as the base specification.

The results on neighbourhood characteristics show different demographic characteristics for each property type. For example, the price of semi-detached or detached houses/bungalows increases with more population aged over 60 while it appears the opposite is true for terrace and end-terrace houses/bungalows. The percentage of family with children turns out to be significant but showing different signs between two submarkets. The percentage of residents over 60 years old also becomes statistically significant and estimates for each submarket are generally consistent with previous results.

Most accessibility variables are consistent across submarkets but some variables are statistically significant only one of submarkets. For example, the distance to the nearest motorway junction and railway. Of environmental variables, railview affects only terrace and end-terrace houses/bungalows while NO is statistically significant in both markets.

Most importantly, landfill variables show consistent results across segmented markets although historical sites are not always statistically significant. It is notable that the coefficient size of active sites increases in both markets. The impact of the proximity to active landfill sites increases to 3.5-3.6% for an additional km.

Chow test statistic determines whether the restriction imposed by the regression using the combined data, namely slope homogeneity, is valid. The null of stability is rejected at the 1% significance level for both divisions. While the results from the divided data sets still show a high degree of similarity, the statistical significance of test results justifies market segmentation based on property construction type.

**Table 3.30: Estimation results of Model 3 for submarkets**

**OLS**
**Segmented market based on construction type**
**Dependent variable: ln(property prices)**

| | all | Semi-detached and Detached | Terrace and End Terrace |
|---|---|---|---|
| ***Structural Variables*** | | | |
| Floor Area | 0.0043*** | 0.0039*** | 0.0049*** |
| | (0.0001) | (0.0002) | (0.0002) |
| Garden Area | 0.0004*** | 0.0003*** | 0.0006*** |
| | (0.0000) | (0.0000) | (0.0000) |
| Sales Date | 0.0002*** | 0.0002*** | 0.0002*** |
| | (0.0000) | (0.0000) | (0.0000) |
| Age | -0.0293*** | -0.0289*** | -0.0255*** |
| | (0.0034) | (0.0042) | (0.0058) |
| Beds | 0.0147*** | 0.0249*** | -0.0074 |
| | (0.0049) | (0.0062) | (0.0075) |

| | | | |
|---|---|---|---|
| WCs | 0.0155*** | 0.0189*** | 0.0109 |
| | (0.0059) | (0.0070) | (0.0098) |
| Floors | -0.1289*** | -0.1369*** | -0.0973*** |
| | (0.0100) | (0.0111) | (0.0198) |
| Garage | 0.1071*** | 0.0871*** | 0.0410*** |
| | (0.0060) | (0.0073) | (0.0109) |
| BG1 | -0.0749 | -0.0442 | -0.1075 |
| | (0.1197) | (0.1582) | (0.1748) |
| BG2 | 0.2912*** | 0.2696*** | 0.4804*** |
| | (0.0855) | (0.0931) | (0.1759) |
| BG3 | -0.1192*** | 0.1450** | -0.0917*** |
| | (0.0187) | (0.0668) | (0.0312) |
| BG4 | -0.0650*** | 0.0200 | -0.0390 |
| | (0.0136) | (0.0200) | (0.0270) |
| BG5 | 0.0329 | 0.0229 | 0.0491 |
| | (0.0335) | (0.0423) | (0.0550) |
| BG8 | 0.0345* | 0.1044*** | 0.0297 |
| | (0.0201) | (0.0330) | (0.0322) |
| BG9 | 0.0818*** | 0.1528*** | -0.3261*** |
| | (0.0288) | (0.0301) | (0.0913) |
| BG10 | -0.3069*** | -0.2358*** | 0.3502 |
| | (0.0455) | (0.0456) | (0.2493) |
| BG19 | 0.1066*** | 0.1100*** | 0.1396* |
| | (0.0240) | (0.0244) | (0.0717) |
| BG20 | -0.1209*** | -0.1237*** | -0.0839*** |
| | (0.0095) | (0.0121) | (0.0222) |
| BG24 | 0.1690*** | 0.1991*** | 0.0480 |
| | (0.0208) | (0.0201) | (0.2429) |
| BG30 | -0.1482*** | -0.1185*** | -0.1893*** |
| | (0.0140) | (0.0162) | (0.0302) |
| BG31 | -0.0860*** | -0.0362** | -0.0983*** |
| | (0.0155) | (0.0183) | (0.0328) |
| BG32 | 0.0779*** | 0.0995*** | 0.1435 |
| | (0.0207) | (0.0225) | (0.0906) |
| BG36 | -0.3427*** | -0.1820 | -0.2857*** |
| | (0.0402) | (0.1593) | (0.0507) |
| ***Neighbourhood Variables*** | | | |
| Age60 | -0.0001 | 0.0021*** | -0.0020** |
| | (0.0005) | (0.0006) | (0.0008) |
| Unemployment | -0.0099*** | -0.0113*** | -0.0063*** |
| | (0.0005) | (0.0008) | (0.0007) |
| White | 0.0049*** | 0.0082*** | 0.0022** |
| | (0.0007) | (0.0012) | (0.0010) |
| Asian | 0.0061*** | 0.0078*** | 0.0032*** |
| | (0.0007) | (0.0013) | (0.0010) |
| Family with children | 0.0004 | 0.0033*** | -0.0021*** |
| | (0.0005) | (0.0006) | (0.0007) |

| | | | |
|---|---|---|---|
| ***Accessibility Variables*** | | | |
| Primary Schools | 0.1607*** | 0.0957*** | 0.1800*** |
| | (0.0177) | (0.0239) | (0.0262) |
| Shops | -0.0156*** | -0.0324*** | 0.0039 |
| | (0.0033) | (0.0049) | (0.0047) |
| Rail Station | -0.0014*** | -0.0014*** | -0.0010** |
| | (0.0003) | (0.0004) | (0.0005) |
| Park | -0.0000 | 0.0000 | 0.0004 |
| | (0.0003) | (0.0004) | (0.0005) |
| University | -0.0026*** | -0.0030*** | -0.0017*** |
| | (0.0003) | (0.0004) | (0.0005) |
| CBD | 0.0007 | 0.0013 | -0.0021 |
| | (0.0014) | (0.0017) | (0.0025) |
| Motorway Junction | 0.0037*** | 0.0010 | 0.0063*** |
| | (0.0012) | (0.0014) | (0.0020) |
| Airport | -0.0076*** | -0.0082*** | -0.0034** |
| | (0.0010) | (0.0014) | (0.0016) |
| Mosque | 0.0358*** | 0.0307*** | 0.0298*** |
| | (0.0043) | (0.0054) | (0.0076) |
| Industry A | 0.0439*** | 0.0382*** | 0.0488*** |
| | (0.0046) | (0.0061) | (0.0078) |
| Industry B | 0.0031 | -0.0041 | -0.0077 |
| | (0.0071) | (0.0090) | (0.0114) |
| Motorway | 0.0037 | 0.0160** | -0.0119 |
| | (0.0048) | (0.0063) | (0.0078) |
| Road A | -0.0289*** | -0.0407*** | -0.0404*** |
| | (0.0083) | (0.0109) | (0.0132) |
| Road B | -0.0203*** | -0.0110 | -0.0078 |
| | (0.0064) | (0.0079) | (0.0112) |
| Minor Road | -0.2982** | -0.0988 | -0.1907 |
| | (0.1327) | (0.1448) | (0.2790) |
| Railway | 0.0150** | 0.0257*** | -0.0008 |
| | (0.0071) | (0.0092) | (0.0115) |
| ***Environmental Variables*** | | | |
| Water View | -0.0000 | 0.0003 | -0.0001 |
| | (0.0003) | (0.0004) | (0.0005) |
| Park View | 0.0000 | 0.0000 | 0.0000 |
| | (0.0001) | (0.0001) | (0.0001) |
| Road View | 0.0002 | 0.0003 | 0.0003 |
| | (0.0003) | (0.0003) | (0.0004) |
| Rail View | -0.0019*** | -0.0019 | -0.0020** |
| | (0.0007) | (0.0013) | (0.0009) |
| Road Noise | -0.0016*** | -0.0020** | -0.0017** |
| | (0.0006) | (0.0008) | (0.0009) |
| Rail Noise | -0.0033* | -0.0036 | -0.0028 |
| | (0.0020) | (0.0034) | (0.0025) |
| Airport Noise | 0.0015 | 0.0054 | 0.0029 |

| | | | |
|---|---|---|---|
| | (0.0026) | (0.0037) | (0.0039) |
| $NO_2$ | 0.0006*** | 0.0004 | 0.0007*** |
| | (0.0002) | (0.0003) | (0.0002) |
| CO | 0.0056 | 0.0015 | 0.0132 |
| | (0.0069) | (0.0090) | (0.0104) |
| ***Ward*** | | | |
| Aston | -0.0700** | 0.0165 | -0.1466*** |
| | (0.0341) | (0.0724) | (0.0450) |
| Bartley Green | -0.0719 | -0.0791 | -0.0164 |
| | (0.0499) | (0.0647) | (0.0810) |
| Billesley | 0.0407 | -0.0378 | 0.1098* |
| | (0.0345) | (0.0447) | (0.0561) |
| Bournville | 0.0585 | 0.0109 | 0.1013 |
| | (0.0417) | (0.0572) | (0.0636) |
| Brandwood | 0.0779* | 0.0112 | 0.1149* |
| | (0.0410) | (0.0559) | (0.0631) |
| Edgbaston | 0.1143*** | 0.0456 | 0.2292*** |
| | (0.0415) | (0.0566) | (0.0640) |
| Erdington | 0.1653*** | 0.1842*** | 0.1045** |
| | (0.0289) | (0.0398) | (0.0430) |
| Fox Hollies | -0.0277 | -0.0159 | 0.0172 |
| | (0.0234) | (0.0338) | (0.0328) |
| Hall Green | 0.0011 | -0.0272 | 0.0772* |
| | (0.0264) | (0.0354) | (0.0400) |
| Handsworth | -0.0020 | 0.2142*** | -0.1648*** |
| | (0.0344) | (0.0541) | (0.0467) |
| Harborne | 0.1658*** | 0.1053* | 0.2486*** |
| | (0.0469) | (0.0625) | (0.0740) |
| Hodge Hill | 0.1492*** | 0.1500*** | 0.0394 |
| | (0.0285) | (0.0383) | (0.0478) |
| King's Norton | 0.0441 | 0.0091 | 0.0864 |
| | (0.0493) | (0.0649) | (0.0772) |
| Kingsbury | 0.1945*** | 0.2185*** | 0.1461*** |
| | (0.0354) | (0.0495) | (0.0512) |
| Kingstanding | 0.1183*** | 0.1800*** | -0.0401 |
| | (0.0329) | (0.0447) | (0.0531) |
| Ladywood | 0.0199 | 0.0634 | -0.0090 |
| | (0.0395) | (0.0576) | (0.0566) |
| Longbridge | 0.1072** | 0.0840 | 0.1244 |
| | (0.0479) | (0.0619) | (0.0772) |
| Moseley | 0.1627*** | 0.1593*** | 0.1704*** |
| | (0.0376) | (0.0512) | (0.0575) |
| Nechells | 0.1043*** | 0.2323*** | 0.0458 |
| | (0.0323) | (0.0621) | (0.0429) |
| Northfield | 0.0156 | -0.0361 | 0.0684 |
| | (0.0463) | (0.0596) | (0.0770) |
| Oscott | 0.0546 | 0.1002** | -0.0390 |

| | | | |
|---|---|---|---|
| | (0.0349) | (0.0453) | (0.0609) |
| Perry Barr | -0.0035 | 0.0397 | -0.1032* |
| | (0.0353) | (0.0468) | (0.0591) |
| Quinton | 0.0310 | -0.0079 | 0.1195 |
| | (0.0485) | (0.0636) | (0.0793) |
| Sandwell | -0.0053 | 0.0970** | -0.1800*** |
| | (0.0328) | (0.0468) | (0.0489) |
| Selly Oak | 0.1110** | -0.0137 | 0.2117*** |
| | (0.0438) | (0.0602) | (0.0669) |
| Shard End | 0.0718** | -0.0026 | 0.1706*** |
| | (0.0325) | (0.0457) | (0.0488) |
| Sheldon | -0.0092 | -0.0598* | 0.0591 |
| | (0.0253) | (0.0314) | (0.0503) |
| Small Heath | 0.0664*** | 0.1409*** | 0.0573* |
| | (0.0246) | (0.0544) | (0.0311) |
| Soho | -0.2161*** | 0.0115 | -0.3045*** |
| | (0.0349) | (0.0689) | (0.0476) |
| Sparkbrook | -0.0453 | 0.0294 | -0.0760* |
| | (0.0344) | (0.0875) | (0.0445) |
| Sparkhill | 0.0650** | 0.2411*** | 0.0417 |
| | (0.0311) | (0.0530) | (0.0415) |
| Stockland Green | 0.0941*** | 0.1191*** | 0.0123 |
| | (0.0311) | (0.0435) | (0.0459) |
| Sutton Four Oaks | 0.5445*** | 0.5520*** | 0.4752*** |
| | (0.0424) | (0.0524) | (0.0849) |
| Sutton New Hall | 0.4413*** | 0.4221*** | 0.4135*** |
| | (0.0317) | (0.0424) | (0.0556) |
| Sutton Vesey | 0.3385*** | 0.3461*** | 0.3462*** |
| | (0.0301) | (0.0399) | (0.0554) |
| Washwood Heath | 0.0375 | 0.1237*** | -0.0118 |
| | (0.0278) | (0.0429) | (0.0386) |
| Weoley | -0.0648 | -0.1218** | -0.0140 |
| | (0.0453) | (0.0596) | (0.0728) |
| Yardley | 0.0397* | 0.0170 | 0.1041*** |
| | (0.0225) | (0.0296) | (0.0356) |
| ***Landfill Variables*** | | | |
| $Active_3$ | -0.0298*** | -0.0364** | -0.0350** |
| | (0.0113) | (0.0149) | (0.0174) |
| $Historic_{11}$ | -0.0251*** | -0.0046 | -0.0340*** |
| | (0.0078) | (0.0104) | (0.0126) |
| $Historic_{12}$ | -0.0240*** | -0.0391*** | -0.0076 |
| | (0.0075) | (0.0098) | (0.0116) |
| $Historic_{13}$ | -0.0371*** | -0.0218*** | -0.0389*** |
| | (0.0048) | (0.0064) | (0.0074) |
| $Historic_{14}$ | 0.0023 | -0.0052 | 0.0070 |
| | (0.0053) | (0.0066) | (0.0085) |
| Constant | 10.5451*** | 10.3610*** | 10.4285*** |

| | | | |
|---|---|---|---|
| | (0.0932) | (0.1414) | (0.1399) |
| ***Diagnostic tests*** | | | |
| ***N*** | 10792 | 5741 | 5051 |
| $R^2$ | | | |
| Adjusted $R^2$ | 0.7564 | 0.7609 | 0.5633 |
| AIC | 0.7542 | 0.7569 | 0.5548 |
| Jarque-bera | 5036 | 4023 | 1700*** |
| Multicollinearity | 0.24358683 | 0.23907216 | 0.43674975 |
| Breusch-Pagan | 23.23*** | 70.08*** | 0.9437*** |
| Ramsey RESET | 94.26*** | 73.97*** | 2.59* |
| **Chow test** | 7.7381589*** | | |

*Notes*: BG25 and BG36 are omitted for collinearity for Terrace and End-terrace group and thus are excluded for all other models so that we can perform a test for stability using Chow tests which requires the same explanatory variables across all submarkets. $F_{0.01}$ (96, 10,600) = 1.3684453 is the critical value of the F distribution at the 1% significance level for F(*k, N-2k*) degrees of freedom where *k* is the number of parameters and *N* is observations.

The spatial expansion model is used to assess variability over space for the estimates of coefficients. The expansion model describes how parameters in the initial model drift in the space spanned by the expansion variables that interact with locational information. The expansion model takes the form (Casetti, 1972):

$$\begin{aligned} y &= \alpha + \beta X + \varepsilon \\ \beta &= ZJ\beta_0 \end{aligned} \qquad \textbf{(3.22)}$$

The second equation is called the "expansion process" since estimates for individual points in space can be derived. Substituting the second equation into the first, the terminal form of the expansion model is:

$$y = \alpha + XZJ\beta_0 + \varepsilon \qquad \textbf{(3.23)}$$

where:

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \qquad X = \begin{pmatrix} x_1' & 0 & \cdots & 0 \\ 0 & x_2' & & \\ \vdots & & \ddots & \\ 0 & & & x_n' \end{pmatrix} \qquad \beta_0 = \begin{pmatrix} \beta_x \\ \beta_y \end{pmatrix} \qquad \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

$$Z = \begin{pmatrix} Z_{x1} \otimes I_k & Z_{y1} \otimes I_k & 0 & \cdots & \cdots & \\ 0 & & \ddots & \ddots & & \\ \vdots & & & \ddots & \ddots & \\ & & & & Z_{x1} \otimes I_k & Z_{y1} \otimes I_k \end{pmatrix} \quad J = \begin{pmatrix} I_k & 0 \\ 0 & I_k \\ \vdots & \\ 0 & I_k \end{pmatrix}$$

$y$ is an $n \times 1$ dependent variable vector and $X$ is an $n \times nk$ matrix consisting of terms $x_i$ representing $k$x$1$ explanatory variable vectors. The locational information is recorded in the matrix $Z$ which has elements $Z_x$ and $Z_y$ which represents $x$, $y$ coordinates for each observation $i$. Given $y$, $X$ and $Z$, the model can be estimated using least-squares to produce estimates of the $2k$ parameters, $\beta_x$ and $\beta_y$.

There are in fact a number of alternative expansion specifications. One approach taken in LeSage's spatial econometrics toolbox for Matlab is to include the base $k$ variables in the matrix $X$ and only $2(k-1)$ variables in expansion form (i.e. interaction terms of explanatory variables with the information on the absolute location) by excluding the constant term from the expansion process. This way, we can partition the influence of explanatory variables into fixed and spatial effects. The empirical model chosen thus is:

$$y = \alpha + \beta X + \beta_1 X Z_x + \beta_2 X Z_y + \varepsilon \qquad \textbf{(3.24)}$$

Then the total impact of explanatory variables on the dependent variable is:

$$\begin{aligned} \gamma_{xi} &= \beta_i + \beta_{xi} Z_x \\ \gamma_{yi} &= \beta_i + \beta_{yi} Z_y \end{aligned} \qquad \textbf{(3.25)}$$

where $\gamma_{xi}$ and $\gamma_{yi}$ show the non-spatial impact as well as the spatially varying impacts in the $x$-$y$ direction. As the parameters change over space in a linear way, the model is also called the locally linear spatial model.

Casetti (1982) further proposes an extended expansion model by including heteroscedastic error terms in the expansion relationship: Drift Analysis of Regression Parameters (DARP) model, taking the form:

$$\begin{aligned} y &= \alpha + \beta X + e \\ \beta &= ZJ\beta_0 + u \end{aligned} \qquad \textbf{(3.26)}$$

Substituting the second equation into the first, this version of the model can be written as a regression of the form:

$$y = \alpha + \beta X + \beta_1 XZ_x + \beta_2 XZ_y + Xu + e \qquad \textbf{(3.27)}$$

The model incorporates the composite disturbance term, $\varepsilon = Xu + e$ where $e$ is the constant component and $Xu$ is the non-constant variance component. The variance structure of the composite disturbance, in general, takes the following variance structure:

$$\sigma_i^2 = g(h_i, \gamma) \qquad \textbf{(3.28)}$$

This represents the variance over space which involves any functional form $g$ of some known variable $h_i$ such as with $x$, $y$ coordinates and associated parameters $\gamma$. The parameter $\gamma$ measures the average impact of the non-constant variance component, $Xu$ in the composite disturbance. The chi-squared distributed statistics are used to test the null of zero value of $\gamma$ parameters. Statistically significant and positive (negative) $\gamma$ implies increasing (decreasing) variance in the stochastic component of the expansion relation over space. Increasing variance would produce larger errors ($u$) in the expansion relationship with movement away from a certain direction. That is, a change in estimated coefficients may diverge from the deterministic expansion specification to a greater extent with distance from that direction. On the other hand, with a negative $\gamma$, the errors made by the deterministic expansion specification become smaller as we move away from a certain direction. In other words, the further away from that direction, the better the expansion relation works in the estimation of locally linear parameters. An insignificant $\gamma$ means that the change in parameters over space adheres strictly to the deterministic expansion specification.

The estimation of the hedonic regressions by DARP is undertaken using ML methods. In Figure 3.13, the total impacts of different landfill variables on house prices are shown while taking into account both the global model non-spatial impact plus the spatial impact indicated by the expansion coefficients in both *x-y* direction. However, the parameters $\gamma$ are insignificant for both *x, y* coordinates, which indicates that the simple deterministic expansion relationship is working well in the west-east and south-north direction without any drift.

The estimates are displayed for each coordinate dimension. The coefficient graphs of *Active3* shows that the number of active sites within 3 km has an increasingly negative impact on property prices moving in the easterly and northerly direction. Among the variables of historical sites however, only *Historic11* (the number of historical sites closed 1-10 years ago) and *Historic13* (the number of historical sites closed over 20 years) show negative impacts on property prices. The adjusted $R^2$ of the expansion model is 0.7851 which is slightly greater than 0.7646, the adjusted $R^2$ of the global non-spatial model for the unified property market.

**Figure 3.13: Spatial *x-y* expansion estimates**

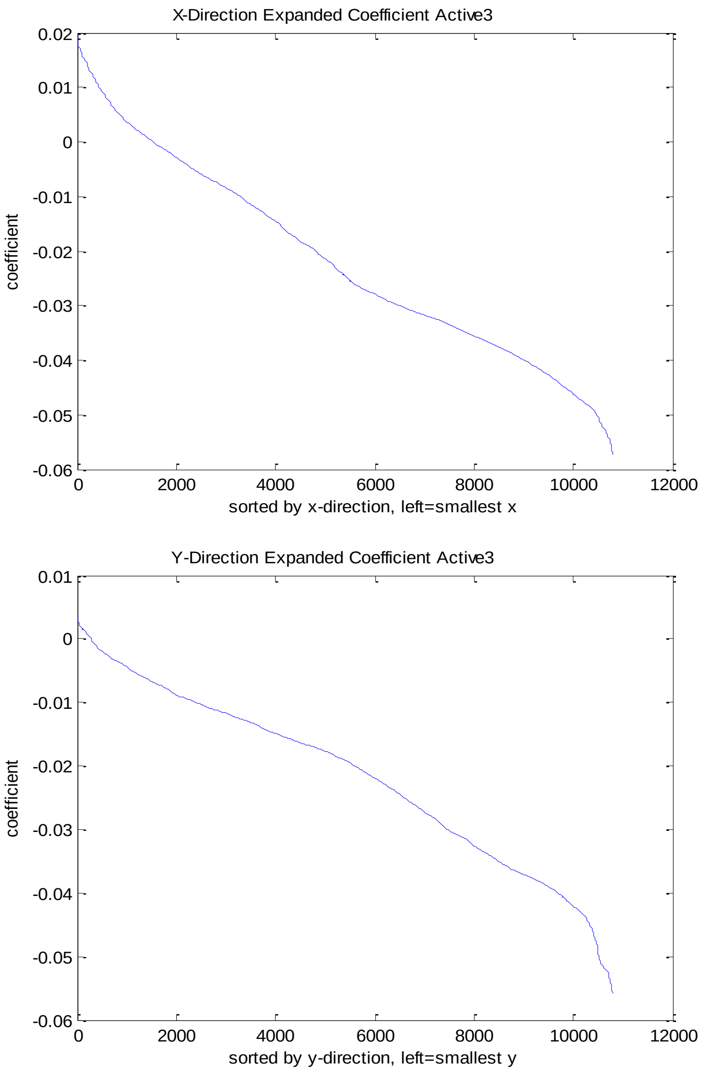


**Figure 3.13-continued**

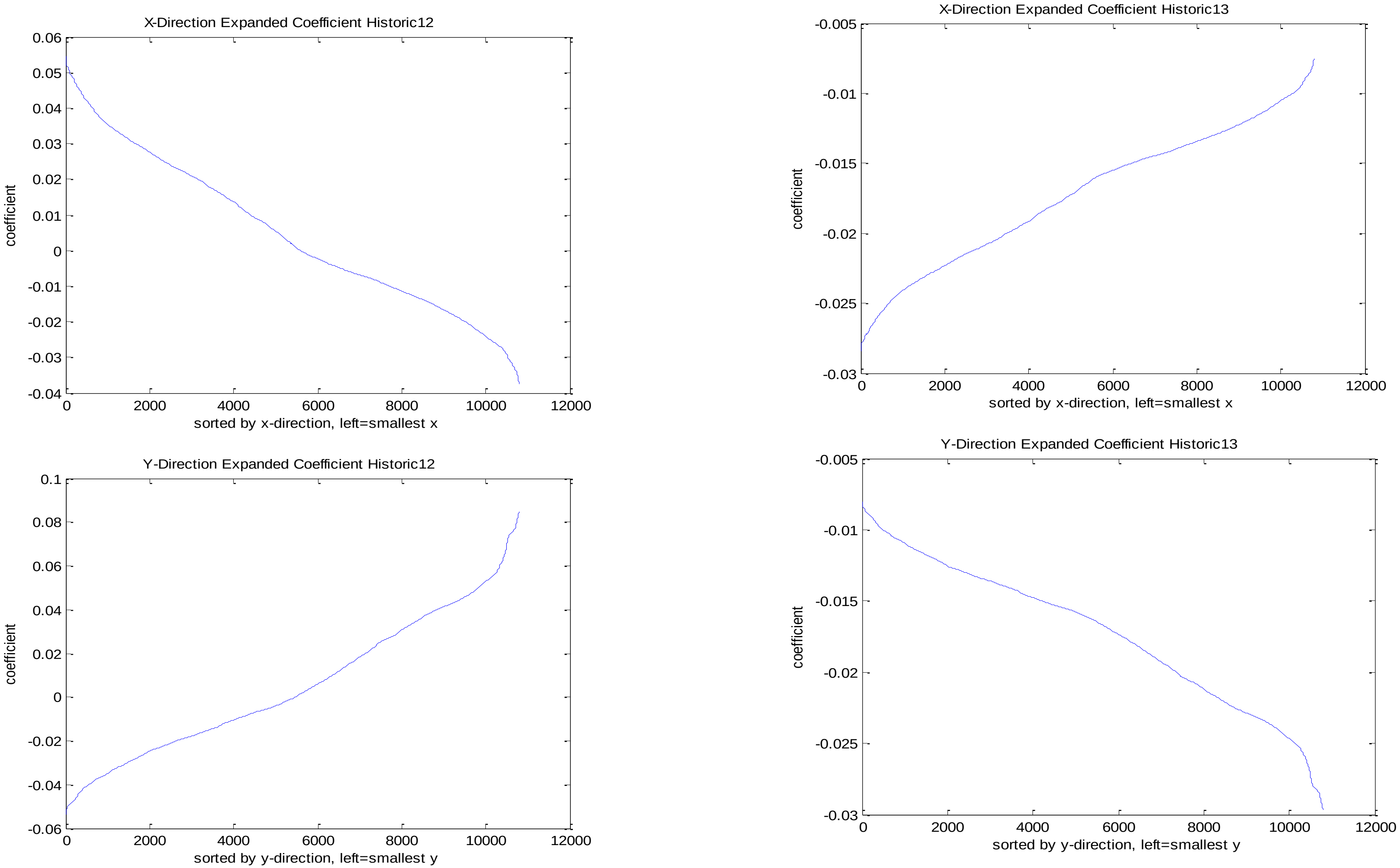
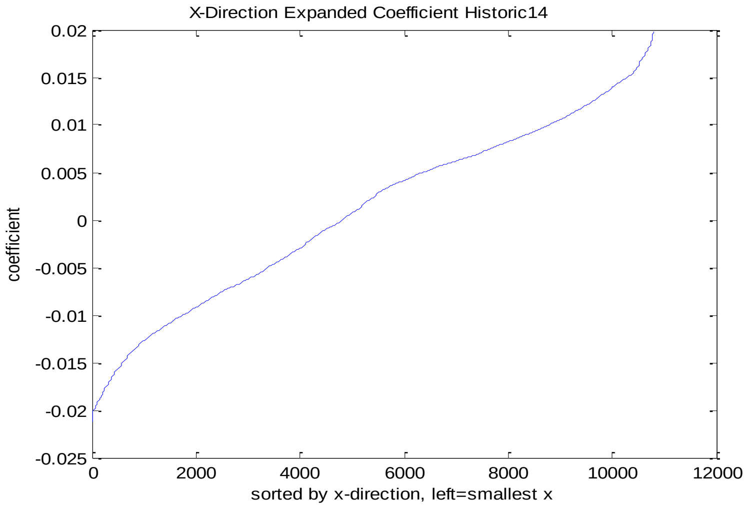
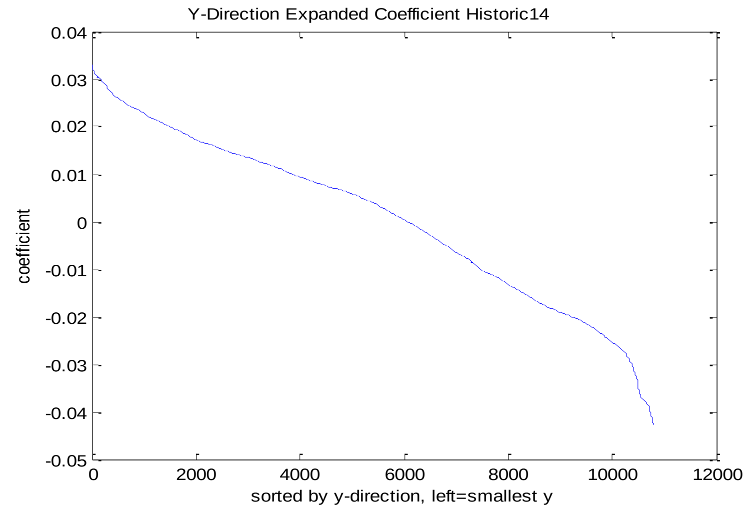


**Figure 3.13-continued**



## 3.6 Conclusion

The rate of environmental taxation should be established at a rate to charge for the social cost of the negative externality associated with waste disposal method. In the case of the landfill tax, this would be the cost of the environmental impacts of landfilling one tonne of a certain type of waste. More accurate measure of landfill disamenity will help policy makers to set a socially optimal rate of landfill tax. By applying the hedonic price technique to a sample of house transactions in Birmingham, this chapter attempts to value the disamenity impact of landfill. Although not an original undertaking, this chapter addresses issues often ignored in the literature and does so moreover using a large hedonic dataset that is comparatively rich in terms of structural, neighbourhood, environmental and accessibility variables. The landfill data includes both historical sites as well as active sites with geographical information and site-specific characteristics like waste type buried and the number of years during which the site was operational.

The database also reveals the presence of multiple landfill sites near to residences. Although this situation must be quite common in large metropolitan areas like Birmingham this is not something that any exiting paper seems to have tackled: modelling landfill dismaenities arising from proximity to multiple sites. Investigating the presence of multiple historical and active landfill sites is the chief advance made in this chapter.

Model 1, which models landfill dismaneity impacts by distance to the nearest active site and ignores historical sites, most closely resembles the specification encountered in the bulk of the literature. The results from Model 1 broadly confirm findings made elsewhere. Proximity to active landfill sites significantly reduces house prices and there is evidence that type of waste that is buried affects the disamenity impact. Whereas only a handful of studies have even considered the role of wind direction in this analysis being downwind of an active landfill site increases the disamenity impact. Arguably this is sufficient to call into question the results of any study neglecting to include wind direction. There is also some evidence that the greater the period of time during which a site has been operational the lower the disamenity impacts. Perhaps the best interpretation of this finding is that sites that have been in operation for longer have a shorter lifetime. Of course it would be better to test this with an explicit measure of lifetime expectancy but such a variable was not available.

Model 2 extends the analysis by including disamenity impacts from both historical and active landfill sites. The dramatic impact that this has on the measured impact of landfill provides strong empirical evidence that it is essential to take account of both. Many existing studies deal only with active landfill sites. The statistical significance of historical landfill sites clearly implies that dismaenity impacts remain even after the site has closed. Currently the literature on this point is uncertain with some studies finding that closed sites have no impact on house prices whereas other studies find a negative impact. As in other studies there is some evidence that the disamenity impact of landfill decreases with distance from the site.

The third model simply counts the number of historical and active sites within a distance band. This modelling approach represents a methodological improvement in that it accounts for a situation in which properties are simultaneously affected by proximity to more than one landfill site. Allowing for this possibility appears to have a material impact on the measured extent of any disamenity impact. This model suggests that the geographical extent of landfill disamenities differs between active and historical sites. It also suggests that landfill sites have long-term disamenity impacts which last for more than 20 years after site closure. Both these findings are new to the literature.

To summarise the empirical evidence contained in this chapter every 1 km closer to a historical landfill site decreases house prices by 3.24-4.70% according to the estimates of

Model 2. This corresponds to an average reduction of about £1,911-£2,773. On a per-site basis according to the estimates of Model 3, house prices are reduced by 3.09% for each additional historical site less than 1 km from the property corresponding to an average reduction of £1,823.

There are significantly bigger disamenity impacts from active sites according to the results of Model 2. Proximity to active sites reduces property values by 9.92-11.06% per kilometre corresponding to on average £5,852-£6,525. On a per-site basis Model 3 indicates that each site within 3 km of the property reduces house prices by around 3.4% or £2,006. These disamenity impacts are significantly larger than those for historical sites mainly because they extend over a larger geographical area.

Because spatial dependence of house prices is frequently observed in hedonic studies, this chapter employs exploratory spatial data analysis. The results reveal strong evidence of spatial clustering in house prices, particularly among low value houses. The role of spatial dependence was analysed further using both spatial error and spatial lag regression techniques. In either case the parameter governing spatial dependence is highly significant. In particular the results suggest that neighbouring properties influence each other's price through unobserved spatial correlation. Thus, the use of spatial error model helps control for the influence of any omitted variables in the hedonic house price equation.

Market segmentation is first investigated by dividing the data based on property construction types: semi-detached and detached house/bungalows and terrace and end terrace houses/ bungalows. The results confirm strong evidence of disamenity impacts from landfill on properties in both segments. Spatial heterogeneity is modelled using the expansion model which permits the regression results to vary across the city. Such an approach, not previously utilised in the hedonic landfill literature, finds that the adverse effect of active sites on property values becomes bigger as we move towards the north and the east.

Whilst the present study conducts as comprehensive analysis as possible there are inevitably some limitations. Many historical landfill sites have missing values. It is unknown precisely when they closed and what they contain. These things are however also unknown to those buying and selling property which may ameliorate the impact that this has on the results. A second limitation is the fact that there is no information on the size of landfills or on the rate at which currently active landfill sites accept waste. Other studies have shown that the size of a landfill is an important determinant of the overall disamenity impact. Turning now to the econometric analysis, the use of non-parametric geographically weighted regressions (GWR) permits more flexible modelling of heterogeneous coefficients over space but this proved to be too difficult in such a large dataset.

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## Appendix 3.1: Data Source

| Variable Name | Source of Information |
|---|---|
| Railway Station | The locations of railway stations were obtained from Railtrack plc. and grid referenced using Land-Line.Plus |
| Park | Any sites with the name "park", "recreation ground" or "common" were identified from the Birmigham A-Z and their outline extracted from Land-Line.Plus |
| University | University and Queen Elizabeth Hospital were located between these 2 facilities adjacent to the University railway station. |
| CBD | Central Business District (DBC) was located in the Bull Ring in the centre of Birmingham |
| Motorway Junction | The data were obtained from OS Land-Line. Plus (Ordnance Survey, 1996) |
| Airport | Birmingham Airport was located on the B4438 at the Birmingham Airport Turn off |
| Mosque | The locations of all mosques in Birmingham were obtained from the web based directory http://www.birminghamuk.com/mosques.htm. These were grid referenced using ADDRESS-POINT |
| Industry A | The locations of all Type A and B industrial process and landfill sites were obtained from Birmingham City Council. This data was collected for the purposes of identifying potential areas of contaminated land |
| Industry B | |
| Motorway | The data were obtained from OS Land-Line. Plus (Ordnance Survey, 1996) |
| A Road | |
| B Road | |
| Minor Road | |
| Railway Line | |
| Primary Schools | The names and addresses of primary schools were determined from the OFFSTED web site and grid referenced using ADDRESS-POINT. The information on school quality was obtained for 1997 from the Department for Education and Employment website http://www.dfee.gov.uk/performance/primary_97.htm |
| Shops | Any businesses registered as “Delicatessens”, “Grocers”, “Newsagents” or “Supermarkets” were obtained from the Yellow Point database. This combines information from the Yellow Pages with ADDRESS-POINT to provide an accurate grid reference for each of these facilities |
| For further information see: Bateman et al. (2004) | |

## Appendix 3.2: Statistics for Spatial Correlation

<u>Univariate Ripley's *K* function</u>

Ripley's *K* function (Ripley, 1977) is a classical tool to analyse spatial point patterns. The univariate *K* function is estimated by the ratio of the average number of neighbours on the density, estimated itself by the total number of points divided by the domain area:

$$K(r) = \lambda^{-1} E\,[\text{number of extra events within distance } r \text{ of a randomly chosen event}] \qquad (1)$$

where $\lambda$ is the density (number per unit area) of events. If $\lambda$ is a constant, points are distributed independently from each other and the point process is called homogeneous is or stationary. The simplest *K(r)* for a homogeneous Poisson process is known as complete spatial randomness:

$$K(r) = \pi r^2 \qquad (2)$$

This value is used as a benchmark. That is, $K(r) > \pi r^2$ indicates that the probability to find a neighbour at the distance is then greater than the probability to find a point in the same area anywhere in the domain: points are aggregated. Inversely, $K(r) < \pi r^2$ indicates that the average neighbour density is smaller than the average point density on the studied domain. Points are dispersed.

Points located close to the domain borders are problematic because a part of the circle inside which points are supposed to be counted is outside the domain. Ignoring this edge effect results in underestimating *K*. Thus, various edge corrections have been suggested; Ripley isotropic correction estimate of *K*, translation-corrected estimate of *K* and border-corrected estimate of *K*.

Bivariate Ripley's *K* function

The bivariate cross *K* function is estimated for a spatial pattern of two sites; historical landfill site and active sites. The bivariate *K* function counts the expected number of points of type *j* either active or historical site) within a given distance of a point of type *i*. In our case, *i* and *j* refer to active and historical site respectively. Formally, the *K(r)* for more than one type of point is:

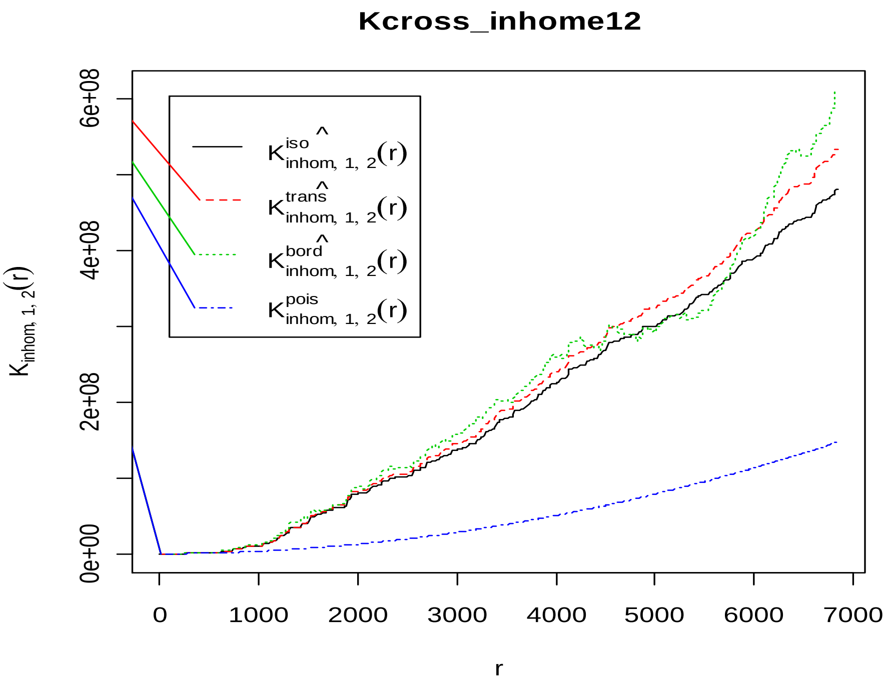
$$K(r) = \lambda_j^{-1} E\,[\text{number of type } j \text{ events within distance } r \text{ of a randomly chosen type } i \text{ event}] \quad (3)$$

For multivariate spatial point pattern where there are *g* types of events, there are $g^2 K$ functions, $K_{11}(r), K_{12}(r), \ldots, K_{1g}(r), K_{21}(r), \ldots, K_{2g}(r), \ldots, K_{gg}(r)$. The "cross-type" (type *i* to type *j*) *K* function of a stationary multi-type point process is defined so that $\lambda_j K_{ij}(r)$ equals the expected number of additional random points of type *j* within a distance *r* of a typical point of type *i* in the process. Here $\lambda_j$ is the density of the type *j* points, i.e. the expected number of points of type *j* per unit area. An estimate of the cross-type $K_{ij}(r)$ is a useful summary statistic in exploratory data analysis of a multi-type point pattern. If the process of type *i* points were independent of the process of type *j* points, then $K_{ij}(r)$ would equal $\pi r^2$. Deviations between the empirical $K_{ij}$ curve and the theoretical curve $\pi r^2$ may suggest dependence between the points of types *i* and *j*.

Furthermore, the cross-type *K* function can be generalized to take into account space heterogeneity (Moller and Waagepetersen, 2003, pp.48-53). Previously, it is assumed that the process can be treated as a realisation of a stationary (spatially homogeneous) random spatial point process in the plane, observed through a bounded window. To estimate the inhomogeneous version of the cross *K* function, the sub-process of points of type *j* is assumed to have intensity function $\lambda_j(u)$ at spatial locations *u*. Suppose we place a mass of $1/\lambda_j(\xi)$ at each point $\xi$ of type $j$. Then the expected total mass per unit area is 1. The inhomogeneous cross-type $K$ function $K_{\text{inhom},ij}(r)$ equals the expected total mass within a radius $r$ of a point of the process of type $i$.

Figure A3.2 displays the results of $K_{\text{inhom},ij}(r)$ with increasing values of distance $r$. The superscripts on $K_{\text{inhom}}(r)$ in the Figure specify methods for correction of edge effects: "iso", "trans" and "border" refer to Ripley isotropic, translation-corrected and border-corrected estimates of $K$ cross respectively. $K^{\text{pois}}_{\text{inhom}}(r)$ is the theoretical value of the cross $K$ function for a marked Poisson process, namely $\pi r^2$. The subscripts of 1 and 2 denote historical sites and active sites respectively. Thus the plots of the cross $K$ indicate the expected number of active sites within a given distance of historical sites, adjusted for spatially varying intensity.

**Figure A3.2: Inhomogeneous Cross *K* Function**




As can be seen in the above figure, all the edge-corrected $K$ estimates are greater than the Poisson process and such deviations become even greater with an increase in distance $r$. This implies historical sites and active sites which are located within 5 km from house sales in Birmingham in 1997 are not spatially independently located.

**Reference**

Moller, J. and Waagepetersen, R. (2003) *Statistical Inference and Simulation for Spatial Point Processes*, Chapman and Hall/CRC Boca Raton.

## Appendix 3.3: Types of Waste Buried

| Type | Description |
|---|---|
| **Inert waste** | Waste which remains largely unaltered once buried such as glass, concrete, bricks, tiles, soil and stones |
| **Industrial waste** | Waste from a factory or industrial process. It excludes waste from mines, quarries and agricultural wastes |
| **Hazardous waste** | Waste that has hazardous properties and is defined in the Special Waste Regulations 1996. Such properties may be flammable, irritant, toxic, harmful, carcinogenic or corrosive |
| **Commercial waste** | Waste from premises used wholly or mainly for trade, business, sport, recreation or entertainment. Excludes household and industrial waste |
| **Liquids/sludge** | Industrial wastewater, sewage sludge and chemical wastes mixed with municipal solid waste |
| **Co-disposal Landfill** | Landfill sites that are licensed to receive municipal solid waste or similar biodegradable wastes and a restricted range of industrial waste (particularly certain suitable special wastes), so that the industrial waste gradually undergoes a form of treatment. Co-disposal ceased under the Landfill Directive |

## Appendix 3.4: Waste Control Measures

| Measure | Description |
|---|---|
| **Gas control** | Landfill gas, which includes methane and carbon dioxide, is produced during the decomposition of waste organic material. Methane is flammable and phyxiant in confined spaces. It is also a GHG. Control measures may include venting the gas away or burning it off |
| **Leachate control** | Leachate is formed when water passes through the waste in the landfill site and becomes contaminated. The water may come from rain, snow or from the waste itself. Control methods such as borehole pumps for extracting the leachate are sometimes necessary to prevent groundwater pollution |

## Appendix 3.5: Box-Cox Transformation

### Table A3.5.1: Estimation results of Model 1

**Box-Cox regression model(applies the Box-Cox transform only to the dependent variable)**
**Total observation: 10792 cross sections**
**Dependent variable: the transform of property prices**

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| ***Structural Variables*** | | | | | | |
| Floor area | 0.0347*** | 0.0347*** | 0.0346*** | 0.0358*** | 0.0348*** | 0.0350*** |
| Garden area | 0.0034*** | 0.0034*** | 0.0034*** | 0.0035*** | 0.0034*** | 0.0035*** |
| Sales Date | 0.0015*** | 0.0015*** | 0.0015*** | 0.0015*** | 0.0015*** | 0.0015*** |
| Age | -0.1968*** | -0.2004*** | -0.1952*** | -0.2072*** | -0.1984*** | -0.1959*** |
| Beds | 0.0735** | 0.0746** | 0.0698* | 0.0786** | 0.0776** | 0.0763** |
| WCs | 0.1039** | 0.1026** | 0.1020** | 0.1029** | 0.1068** | 0.1043** |
| Floors | -1.2855*** | -1.2878*** | -1.2785*** | -1.3167*** | -1.2919*** | -1.2987*** |
| Garage | 0.5709*** | 0.5700*** | 0.5711*** | 0.5881*** | 0.5772*** | 0.5742*** |
| Detached Bungalow | 0.1645 | 0.1606 | 0.1701 | 0.1697 | 0.1583 | 0.1656 |
| Semi-Detached Bungalow | -0.8052*** | -0.7949*** | -0.8056*** | -0.8977*** | -0.8411*** | -0.8139*** |
| End Terrace Bungalow | -1.9305** | -1.8975** | -1.9303** | -1.9041** | -1.9073** | -1.9229** |
| Terrace Bungalow | -0.7650 | -0.8043 | -0.7919 | -0.8951 | -0.8441 | -0.7830 |
| Detached House | 1.1328*** | 1.1218*** | 1.1265*** | 1.1597*** | 1.1315*** | 1.1428*** |
| End Terrace House | -0.6777*** | -0.6764*** | -0.6743*** | -0.7040*** | -0.6881*** | -0.6873*** |
| Terrace House | -0.7240*** | -0.7277*** | -0.7160*** | -0.7401*** | -0.7274*** | -0.7310*** |
| BG1 | -0.4529 | -0.4337 | -0.4470 | -0.4389 | -0.5138 | -0.4682 |
| BG2 | 2.1891*** | 2.1752*** | 2.1721*** | 2.2866*** | 2.2294*** | 2.1850*** |
| BG3 | -0.4007*** | -0.3910*** | -0.3815** | -0.3996*** | -0.4074*** | -0.3971*** |
| BG4 | -0.0684 | -0.0616 | -0.0564 | -0.0583 | -0.0700 | -0.0672 |
| BG5 | 0.4293* | 0.4356* | 0.4604* | 0.4347* | 0.4350* | 0.4290* |
| BG8 | 0.5837*** | 0.5863*** | 0.6331*** | 0.5995*** | 0.5893*** | 0.5845*** |
| BG9 | 0.8846*** | 0.8826*** | 0.8777*** | 0.9537*** | 0.8867*** | 0.8955*** |
| BG10 | -2.0641*** | -2.0667*** | -2.0557*** | -2.1085*** | -2.0857*** | -2.0992*** |
| BG19 | 0.8930*** | 0.8982*** | 0.8847*** | 0.9774*** | 0.9258*** | 0.9047*** |
| BG20 | -0.7766*** | -0.7774*** | -0.7633*** | -0.7563*** | -0.7483*** | -0.7728*** |
| BG24 | 1.1296*** | 1.1380*** | 1.1207*** | 1.1891*** | 1.1324*** | 1.1416*** |
| BG25 | -4.7920*** | -4.7870*** | -4.7170*** | -4.9785*** | -4.9176*** | -4.8282*** |
| BG30 | -1.0498*** | -1.0538*** | -1.0458*** | -1.1272*** | -1.0656*** | -1.0631*** |
| BG31 | -0.4881*** | -0.5032*** | -0.4702*** | -0.5154*** | -0.4858*** | -0.4788*** |
| BG32 | 0.6107*** | 0.5945*** | 0.6109*** | 0.6029*** | 0.5857*** | 0.6280*** |
| BG35 | 1.0101* | 0.9751* | 0.9892* | 0.9616* | 0.9389* | 1.0018* |
| BG36 | -1.7915*** | -1.7918*** | -1.7662*** | -1.8641*** | -1.7924*** | -1.7874*** |
| ***Neighbourhood Variables*** | | | | | | |
| Age60 | 0.0064* | 0.0063* | 0.0060 | 0.0060 | 0.0064* | 0.0068* |
| Unemployment | -0.0699*** | -0.0701*** | -0.0698*** | -0.0719*** | -0.0701*** | -0.0703*** |
| White | 0.0335*** | 0.0334*** | 0.0338*** | 0.0342*** | 0.0333*** | 0.0326*** |
| Asian | 0.0411*** | 0.0410*** | 0.0396*** | 0.0420*** | 0.0409*** | 0.0403*** |
| Family with children | 0.0059 | 0.0057 | 0.0059* | 0.0050 | 0.0056 | 0.0060 |
| ***Accessibility Variables*** | | | | | | |
| Primary Schools | 1.3215*** | 1.3378*** | 1.3314*** | 1.3356*** | 1.3518*** | 1.3255*** |
| Shops | -0.0842*** | -0.0812*** | -0.0777*** | -0.0849*** | -0.0828*** | -0.0838*** |
| Rail Station | -0.0060*** | -0.0063*** | -0.0052** | -0.0075*** | -0.0074*** | -0.0072*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| Park | 0.0002 | 0.0001 | 0.0005 | 0.0009 | 0.0007 | 0.0002 |
| University | -0.0180*** | -0.0174*** | -0.0180*** | -0.0216*** | -0.0198*** | -0.0187*** |
| CBD | -0.0014 | -0.0025 | -0.0001 | 0.0086 | -0.0055 | -0.0023 |
| Motorway Junction | 0.0224*** | 0.0231*** | 0.0217** | 0.0222** | 0.0300*** | 0.0246*** |
| Airport | -0.0568*** | -0.0564*** | -0.0570*** | -0.0616*** | -0.0575*** | -0.0580*** |
| Mosque | 0.2744*** | 0.2725*** | 0.2652*** | 0.2788*** | 0.2939*** | 0.2924*** |
| Industry A | 0.3723*** | 0.3726*** | 0.3742*** | 0.4054*** | 0.4013*** | 0.3534*** |
| Industry B | -0.0100 | -0.0145 | -0.0020 | -0.0517 | -0.0335 | 0.0160 |
| Motorway | 0.0501 | 0.0447 | 0.0445 | 0.0253 | 0.0123 | 0.0368 |
| Road A | -0.1441** | -0.1435** | -0.1344** | -0.1577** | -0.1479** | -0.1425** |
| Road B | -0.0397 | -0.0369 | -0.0459 | -0.0334 | -0.0428 | -0.0351 |
| Minor Road | -0.9241 | -0.8746 | -0.8548 | -0.8528 | -0.9933 | -0.9013 |
| Railway | 0.0257 | 0.0345 | 0.0234 | 0.1067* | 0.0493 | 0.0427 |
| ***Neighbourhood Variables*** | | | | | | |
| Water View | 0.0000 | -0.0001 | 0.0004 | -0.0006 | -0.0002 | -0.0003 |
| Park View | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0001 |
| Road View | 0.0002 | 0.0002 | 0.0002 | 0.0007 | 0.0005 | 0.0004 |
| Rail View | -0.0157*** | -0.0157*** | -0.0163*** | -0.0147*** | -0.0142*** | -0.0154*** |
| Road Noise | -0.0180*** | -0.0181*** | -0.0183*** | -0.0200*** | -0.0189*** | -0.0187*** |
| Rail Noise | -0.0179 | -0.0170 | -0.0166 | -0.0212 | -0.0227 | -0.0191 |
| Airport Noise | 0.0155 | 0.0156 | 0.0184 | 0.0031 | 0.0091 | 0.0042 |
| $NO_2$ | 0.0050*** | 0.0051*** | 0.0044*** | 0.0042*** | 0.0044*** | 0.0051*** |
| CO | 0.0714 | 0.0690 | 0.0840 | 0.0865 | 0.0924* | 0.0620 |
| ***Ward*** | | | | | | |
| Aston | -0.2969 | -0.3047 | -0.4123 | -0.1517 | -0.2990 | -0.1706 |
| Bartley Green | -0.6542* | -0.6535* | -0.7369* | -0.6505* | -0.6286 | -0.5795 |
| Billesley | 0.3399 | 0.3863 | 0.3621 | 0.1171 | 0.2228 | 0.4316* |
| Bournville | 0.4668 | 0.5086 | 0.4227 | 0.2800 | 0.4305 | 0.5535* |
| Brandwood | 0.3414 | 0.3760 | 0.3126 | 0.0852 | 0.2039 | 0.4127 |
| Edgbaston | 1.2603*** | 1.2962*** | 1.2563*** | 1.3811*** | 1.2612*** | 1.3704*** |
| Erdington | 1.1752*** | 1.1433*** | 1.1813*** | 1.5576*** | 1.3263*** | 1.3259*** |
| Fox Hollies | 0.1305 | 0.1781 | 0.1414 | 0.0548 | 0.0712 | 0.0634 |
| Hall Green | 0.1837 | 0.2232 | 0.2014 | 0.0815 | 0.0697 | 0.1793 |
| Handsworth | 0.0622 | 0.0727 | 0.2068 | 0.2669 | 0.0737 | 0.2029 |
| Harborne | 1.4829*** | 1.5199*** | 1.4232*** | 1.7807*** | 1.4965*** | 1.5726*** |
| Hodge Hill | 1.0191*** | 1.0081*** | 1.0018*** | 1.3334*** | 1.1238*** | 1.2050*** |
| King's Norton | 0.3377 | 0.3713 | 0.3115 | -0.0172 | 0.4065 | 0.4228 |
| Kingsbury | 1.3114*** | 1.2905*** | 1.3025*** | 1.5525*** | 1.2794*** | 1.5309*** |
| Kingstanding | 0.8123*** | 0.7646*** | 0.7847*** | 1.0637*** | 0.8683*** | 0.9732*** |
| Ladywood | 0.2557 | 0.2916 | 0.2790 | 0.5741* | 0.3579 | 0.3647 |
| Longbridge | 1.0517*** | 1.1263*** | 1.0823*** | 0.9281** | 1.1704*** | 1.1467*** |
| Moseley | 1.2019*** | 1.2437*** | 1.1542*** | 1.3827*** | 1.2946*** | 1.3702*** |
| Nechells | 0.8872*** | 0.9248*** | 0.8923*** | 1.0868*** | 0.9208*** | 1.0191*** |
| Northfield | 0.1756 | 0.2132 | 0.1712 | -0.1053 | 0.3228 | 0.2805 |
| Oscott | 0.0725 | 0.0650 | 0.0501 | 0.1075 | -0.0374 | 0.1759 |
| Perry Barr | -0.3022 | -0.3148 | -0.2726 | -0.3450 | -0.4961* | -0.2779 |
| Quinton | 0.1238 | 0.1279 | 0.0597 | 0.5243 | 0.1472 | 0.2385 |
| Sandwell | -0.1760 | -0.1635 | -0.1298 | -0.2753 | -0.3139 | -0.1529 |
| Selly Oak | 0.6959** | 0.7313** | 0.6531** | 0.8816*** | 0.8217** | 0.7974** |
| Shard End | 0.3857 | 0.3516 | 0.3520 | 0.5714** | 0.3374 | 0.5607** |
| Sheldon | -0.1039 | -0.0965 | -0.0821 | -0.0483 | -0.0687 | -0.1406 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Small Heath | 0.3848** | 0.4305** | 0.4640*** | 0.5908*** | 0.4863*** | 0.5131*** |
| Soho | -1.4766*** | -1.4695*** | -1.4179*** | -1.3272*** | -1.4026*** | -1.3503*** |
| Sparkbrook | -0.2029 | -0.1099 | -0.1292 | -0.0593 | -0.1723 | -0.0749 |
| Sparkhill | 0.3541 | 0.4053* | 0.4023* | 0.5685** | 0.4850** | 0.4801** |
| Stockland Green | 0.5935** | 0.5575** | 0.6042*** | 0.8757*** | 0.6638*** | 0.7521*** |
| Sutton Four Oaks | 4.0907*** | 4.0244*** | 4.0514*** | 4.4239*** | 4.2309*** | 4.2831*** |
| Sutton New Hall | 3.1357*** | 3.0761*** | 3.0868*** | 3.4793*** | 3.0206*** | 3.4624*** |
| Sutton Vesey | 2.2778*** | 2.2185*** | 2.2470*** | 2.6767*** | 2.3416*** | 2.4587*** |
| Washwood Heath | 0.3438* | 0.3514* | 0.3233 | 0.5607*** | 0.4022* | 0.4972** |
| Weoley | -0.4549 | -0.4296 | -0.5126 | -0.7552** | -0.3837 | -0.3610 |
| Yardley | 0.3130* | 0.2944* | 0.3198* | 0.4020** | 0.3291** | 0.3061* |
| ***Landfill Variables*** | | | | | | |
| *Dist* | 0.1050*** | 0.1132*** | 0.5506 | 0.0029 | 0.1749*** | 0.1084*** |
| *Downwind* | | 0.0011*** | | | | |
| (1-2 km)· *Dist* | | | -0.1536 | | | |
| (2-3 km)· *Dist* | | | -0.4618 | | | |
| (3-4 km)· *Dist* | | | -0.4037 | | | |
| (Over 4 km)· *Dist* | | | -0.4246 | | | |
| A05· *Dist* | | | | 0.1384*** | | |
| A06· *Dist* | | | | -0.0146 | | |
| A07· *Dist* | | | | 0.0575*** | | |
| (Year_5-10)· *Dist* | | | | | -0.1052*** | |
| (Year_over10)· *Dist* | | | | | -0.0489** | |
| *Operated year* | | | | | | 0.0205*** |
| Constant | 33.1272 | 32.9188 | 32.8478 | 34.2075 | 33.4958 | 33.1974 |
| | | | | | | |
| **θ** | 0.1902*** | 0.1901*** | 0.1896*** | 0.1927*** | 0.1904*** | 0.1909*** |
| **sigma** | 1.8108 | 1.8078 | 1.7974 | 1.8545 | 1.8109 | 1.8235 |

*Notes*: Box-Cox transformation is not applied to explanatory variables. Likelihood ratio (LR) tests are used for the significance of each variable as well as to test appropriateness of alternative forms. For the Box-Cox parameter, the hypotheses that θ is -1, 0 and 1 correspond to the reciprocal, the log, and no transformation at all.

## Table A3.5.2: Estimation results of Model 2

**Box-Cox regression model(applies the Box-Cox transform only to the dependent variable)**
**Total observation: 10792 cross sections**
**Dependent variable: the transform of property prices**

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| ***Structural Variables*** | | | | | | |
| Floor area | 0.0341*** | 0.0340*** | 0.0341*** | 0.0345*** | 0.0341*** | 0.0341*** |
| Garden area | 0.0034*** | 0.0033*** | 0.0034*** | 0.0034*** | 0.0034*** | 0.0034*** |
| Sales Date | 0.0015*** | 0.0015*** | 0.0015*** | 0.0015*** | 0.0015*** | 0.0015*** |
| Age | -0.1865*** | -0.1867*** | -0.1901*** | -0.1904*** | -0.1846*** | -0.1868*** |
| Beds | 0.0711* | 0.0718* | 0.0806** | 0.0728* | 0.0738** | 0.0736** |
| WCs | 0.0958** | 0.0954** | 0.0930** | 0.0984** | 0.0973** | 0.0976** |
| Floors | -1.2646*** | -1.2623*** | -1.2623*** | -1.2861*** | -1.2673*** | -1.2644*** |
| Garage | 0.5632*** | 0.5625*** | 0.5688*** | 0.5731*** | 0.5628*** | 0.5682*** |
| Detached | 0.1384 | 0.1409 | 0.1298 | 0.1249 | 0.1280 | 0.1409 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Bungalow | | | | | | |
| Semi-Detached Bungalow | -0.7919*** | -0.7944*** | -0.7902*** | -0.8087*** | -0.8072*** | -0.7956*** |
| End Terrace Bungalow | -1.8733** | -1.8679** | -1.8744** | -1.8724** | -1.8532** | -1.8646** |
| Terrace Bungalow | -0.6947 | -0.6826 | -0.6884 | -0.7211 | -0.6800 | -0.6498 |
| Detached House | 1.1205*** | 1.1187*** | 1.1218*** | 1.1499*** | 1.1405*** | 1.1291*** |
| End Terrace House | -0.6667*** | -0.6637*** | -0.6692*** | -0.6705*** | -0.6670*** | -0.6665*** |
| Terrace House | -0.7189*** | -0.7169*** | -0.7169*** | -0.7333*** | -0.7281*** | -0.7210*** |
| BG1 | -0.3907 | -0.3693 | -0.3771 | -0.3769 | -0.4143 | -0.3877 |
| BG2 | 2.1538*** | 2.1573*** | 2.1660*** | 2.1414*** | 2.1315*** | 2.1756*** |
| BG3 | -0.4267*** | -0.4267*** | -0.4253*** | -0.4361*** | -0.4547*** | -0.4286*** |
| BG4 | -0.0806 | -0.0801 | -0.0870 | -0.0809 | -0.0860 | -0.0811 |
| BG5 | 0.4271* | 0.4201* | 0.4583* | 0.4369* | 0.4387* | 0.4172* |
| BG8 | 0.6039*** | 0.6024*** | 0.5804*** | 0.6337*** | 0.6398*** | 0.5958*** |
| BG9 | 0.8424*** | 0.8316*** | 0.8310*** | 0.8564*** | 0.8390*** | 0.8550*** |
| BG10 | -2.0697*** | -2.0559*** | -2.0778*** | -2.0185*** | -2.0618*** | -2.0716*** |
| BG19 | 0.8917*** | 0.8907*** | 0.9169*** | 0.9096*** | 0.8977*** | 0.8922*** |
| BG20 | -0.7466*** | -0.7452*** | -0.7468*** | -0.7443*** | -0.7355*** | -0.7466*** |
| BG24 | 1.1350*** | 1.1318*** | 1.1488*** | 1.1657*** | 1.1407*** | 1.1318*** |
| BG25 | -4.7338*** | -4.7145*** | -4.8021*** | -4.7282*** | -4.7171*** | -4.7368*** |
| BG30 | -1.0128*** | -1.0103*** | -1.0268*** | -1.0195*** | -1.0099*** | -1.0032*** |
| BG31 | -0.4582*** | -0.4591*** | -0.4547*** | -0.4622*** | -0.4519*** | -0.4609*** |
| BG32 | 0.6152*** | 0.6107*** | 0.6417*** | 0.6080*** | 0.6232*** | 0.6168*** |
| BG35 | 0.9885* | 0.9869* | 0.9717* | 1.0413* | 1.0661** | 0.9968* |
| BG36 | -1.8314*** | -1.8389*** | -1.8624*** | -1.8590*** | -1.8600*** | -1.8538*** |
| ***Neighbourhood Variables*** | | | | | | |
| Age60 | 0.0061 | 0.0060 | 0.0061 | 0.0071* | 0.0059 | 0.0061 |
| Unemployment | -0.0700*** | -0.0700*** | -0.0700*** | -0.0715*** | -0.0721*** | -0.0705*** |
| White | 0.0387*** | 0.0388*** | 0.0385*** | 0.0380*** | 0.0389*** | 0.0376*** |
| Asian | 0.0441*** | 0.0442*** | 0.0447*** | 0.0447*** | 0.0455*** | 0.0435*** |
| Family with children | 0.0056 | 0.0056 | 0.0050 | 0.0056 | 0.0051 | 0.0052 |
| ***Accessibility Variables*** | | | | | | |
| Primary Schools | 1.2284*** | 1.2257*** | 1.2122*** | 1.2888*** | 1.2538*** | 1.2575*** |
| Shops | -0.1019*** | -0.1015*** | -0.1113*** | -0.1168*** | -0.1123*** | -0.1068*** |
| Rail Station | -0.0062*** | -0.0062*** | -0.0063*** | -0.0060*** | -0.0065*** | -0.0066*** |
| Park | 0.0002 | 0.0003 | -0.0006 | 0.0022 | 0.0023 | 0.0015 |
| University | -0.0183*** | -0.0183*** | -0.0198*** | -0.0190*** | -0.0189*** | -0.0192*** |
| CBD | 0.0008 | 0.0011 | 0.0071 | -0.0053 | -0.0005 | 0.0019 |
| Motorway Junction | 0.0227*** | 0.0225*** | 0.0238*** | 0.0261*** | 0.0194** | 0.0251*** |
| Airport | -0.0491*** | -0.0493*** | -0.0545*** | -0.0473*** | -0.0464*** | -0.0522*** |
| Mosque | 0.2532*** | 0.2537*** | 0.2670*** | 0.2689*** | 0.2600*** | 0.2622*** |
| Industry A | 0.3289*** | 0.3302*** | 0.3499*** | 0.3509*** | 0.3393*** | 0.3395*** |
| Industry B | -0.0248 | -0.0282 | -0.0296 | -0.0411 | -0.0340 | -0.0281 |
| Motorway | 0.0885** | 0.0885** | 0.0746** | 0.0699* | 0.0802** | 0.0807** |
| Road A | -0.1695*** | -0.1719*** | -0.1764*** | -0.1880*** | -0.1825*** | -0.1769*** |
| Road B | -0.0558 | -0.0528 | -0.0622 | -0.0464 | -0.0468 | -0.0503 |
| Minor Road | -0.8160 | -0.8300 | -0.9103 | -0.9199 | -1.1884 | -0.9380 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Railway | 0.0578 | 0.0581 | 0.0811 | 0.0401 | 0.0519 | 0.0622 |
| ***Neighbourhood Variables*** | | | | | | |
| Water View | 0.0002 | 0.0002 | 0.0004 | -0.0001 | -0.0001 | 0.0001 |
| Park View | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0001 | 0.0000 |
| Road View | 0.0005 | 0.0004 | 0.0007 | 0.0009 | 0.0006 | 0.0005 |
| Rail View | -0.0151*** | -0.0150*** | -0.0154*** | -0.0151*** | -0.0156*** | -0.0149*** |
| Road Noise | -0.0168*** | -0.0168*** | -0.0165*** | -0.0165*** | -0.0162*** | -0.0167*** |
| Rail Noise | -0.0172 | -0.0173 | -0.0177 | -0.0186 | -0.0169 | -0.0182 |
| Airport Noise | 0.0258 | 0.0256 | 0.0230 | 0.0343* | 0.0239 | 0.0309 |
| $NO_2$ | 0.0051*** | 0.0051*** | 0.0053*** | 0.0047*** | 0.0051*** | 0.0050*** |
| CO | 0.0769 | 0.0774 | 0.0830 | 0.0827 | 0.0921* | 0.0831 |
| ***Ward*** | | | | | | |
| Aston | -0.6256** | -0.6136** | -0.7027*** | -0.8136*** | -0.8000*** | -0.6212** |
| Bartley Green | -0.4386 | -0.4203 | -0.5972 | -0.5450 | -0.5320 | -0.3736 |
| Billesley | 0.1712 | 0.1743 | 0.1102 | 0.0721 | 0.0841 | 0.2284 |
| Bournville | 0.5259* | 0.5349* | 0.5006 | 0.4029 | 0.4316 | 0.5109* |
| Brandwood | 0.3113 | 0.3267 | 0.3381 | 0.2649 | 0.3212 | 0.3703 |
| Edgbaston | 0.9780*** | 0.9977*** | 0.9798*** | 0.8772*** | 1.0532*** | 1.1071*** |
| Erdington | 1.2092*** | 1.2150*** | 1.2426*** | 1.2336*** | 1.2099*** | 1.2584*** |
| Fox Hollies | -0.1594 | -0.1545 | -0.0792 | -0.2440 | -0.2122 | -0.2440 |
| Hall Green | -0.0650 | -0.0611 | -0.0532 | -0.2192 | -0.1970 | -0.0029 |
| Handsworth | -0.0233 | -0.0212 | -0.0694 | -0.2848 | -0.3070 | -0.1154 |
| Harborne | 1.4794*** | 1.4955*** | 1.3541*** | 1.3190*** | 1.4441*** | 1.5135*** |
| Hodge Hill | 1.0905*** | 1.1039*** | 1.1107*** | 1.0494*** | 1.1033*** | 1.1322*** |
| King's Norton | 0.3414 | 0.3442 | 0.3038 | 0.1634 | 0.1810 | 0.3520 |
| Kingsbury | 1.3618*** | 1.3688*** | 1.3844*** | 1.3607*** | 1.3375*** | 1.3991*** |
| Kingstanding | 0.8775*** | 0.8817*** | 0.8477*** | 0.9610*** | 0.9081*** | 0.9616*** |
| Ladywood | 0.2092 | 0.2283 | 0.1195 | -0.0693 | 0.1569 | 0.2903 |
| Longbridge | 0.8291** | 0.8532** | 0.8583** | 0.7533** | 0.7666** | 0.8906** |
| Moseley | 1.0657*** | 1.0692*** | 1.1283*** | 0.9228*** | 0.9938*** | 1.1324*** |
| Nechells | 0.7067*** | 0.7283*** | 0.7396*** | 0.6493*** | 0.6301*** | 0.7650*** |
| Northfield | 0.1350 | 0.1480 | 0.1438 | -0.0610 | 0.1137 | 0.1098 |
| Oscott | 0.2316 | 0.2379 | 0.1979 | 0.0783 | 0.1032 | 0.2843 |
| Perry Barr | -0.1684 | -0.1625 | -0.2033 | -0.3112 | -0.2846 | -0.1046 |
| Quinton | 0.2179 | 0.2348 | 0.0903 | 0.0180 | 0.1690 | 0.2717 |
| Sandwell | -0.0658 | -0.0588 | -0.1065 | -0.2232 | -0.1344 | -0.1158 |
| Selly Oak | 0.6853** | 0.7021** | 0.6178* | 0.6769** | 0.6778** | 0.7477** |
| Shard End | 0.5502** | 0.5635** | 0.5467** | 0.5738** | 0.6522*** | 0.5987** |
| Sheldon | -0.1649 | -0.1626 | -0.2440 | 0.0300 | -0.0329 | -0.1330 |
| Small Heath | 0.4435** | 0.4576*** | 0.4629*** | 0.3630** | 0.4055** | 0.4621*** |
| Soho | -1.2682*** | -1.2642*** | -1.3093*** | -1.5060*** | -1.4551*** | -1.2856*** |
| Sparkbrook | -0.2164 | -0.2038 | -0.1988 | -0.2628 | -0.2146 | -0.1243 |
| Sparkhill | 0.4420** | 0.4490** | 0.4285* | 0.3732* | 0.4447** | 0.4332* |
| Stockland Green | 0.5561** | 0.5713** | 0.5302** | 0.5353** | 0.5660** | 0.6532*** |
| Sutton Four Oaks | 4.0043*** | 4.0017*** | 4.1149*** | 4.0678*** | 4.0409*** | 4.0901*** |
| Sutton New Hall | 3.1310*** | 3.1307*** | 3.1782*** | 3.1715*** | 3.1498*** | 3.1721*** |
| Sutton Vesey | 2.3971*** | 2.4002*** | 2.4271*** | 2.4327*** | 2.4237*** | 2.4795*** |
| Washwood Heath | 0.1478 | 0.1657 | 0.1472 | 0.0469 | 0.1177 | 0.1936 |
| Weoley | -0.3526 | -0.3344 | -0.4619 | -0.4964 | -0.4764 | -0.3263 |
| Yardley | 0.2663* | 0.2781* | 0.2053 | 0.3426** | 0.2875* | 0.2997* |
| ***Landfill Variables*** | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| *Dist* | 0.2506*** | 0.2512*** | 0.5287*** | 0.3372*** | 0.3802*** | 0.2917*** |
| Active· *Dist* | 0.5131*** | 0.5198*** | 0.4978*** | 0.4038** | 0.4055** | 0.5954*** |
| *Downwind* | | 0.0005 | | | | |
| (1-2 km)· *Dist* | | | -0.1229** | | | |
| (2-3 km)· *Dist* | | | -0.3861*** | | | |
| (3-4 km)· *Dist* | | | -0.0369 | | | |
| Inert· *Dist* | | | | -0.2122*** | | |
| Industrial· *Dist* | | | | 0.0458 | | |
| Commercial· *Dist* | | | | -0.1254* | | |
| Household· *Dist* | | | | -0.0193 | | |
| Hazardous· *Dist* | | | | -0.2104 | | |
| Liquids/Sludge· *Dist* | | | | 0.0271 | | |
| Co-disposal· *Dist* | | | | | -0.2118*** | |
| Year_5-10· *Dist* | | | | | | -0.1144 |
| (Year_10-20)· *Dist* | | | | | | -0.0521 |
| (Year_over 20)· *Dist* | | | | | | -0.1189 |
| (Year_unknown)· *Dist* | | | | | | 0.0386 |
| Constant | 32.3426 | 32.2445 | 32.5803 | 33.0151 | 32.6288 | 32.6547 |
| **θ** | 0.1888*** | 0.1886*** | 0.1894*** | 0.1906*** | 0.1898*** | 0.1892*** |
| **Sigma** | 1.7789 | 1.7759 | 1.7882 | 1.8130 | 1.7963 | 1.7857 |

*Notes*: See notes for Table A3.5.1.

## Table A3.5.3: Estimation results of Model 3

**Box-Cox regression model(applies the Box-Cox transform only to the dependent variable)**
**Total observation: 10792 cross sections**
**Dependent variable: the transform of property prices**

| | 1 km | 2 km | 3 km | 4 km | Best |
|---|---|---|---|---|---|
| ***Structural Variables*** | | | | | |
| Floor area | 0.0340*** | 0.0354*** | 0.0345*** | 0.0345*** | 0.0340*** |
| Garden area | 0.0034*** | 0.0035*** | 0.0034*** | 0.0034*** | 0.0034*** |
| Sales Date | 0.0015*** | 0.0016*** | 0.0015*** | 0.0015*** | 0.0015*** |
| Age | -0.1861*** | -0.2009*** | -0.1935*** | -0.1905*** | -0.1865*** |
| Beds | 0.0722** | 0.0677* | 0.0730** | 0.0683* | 0.0716* |
| WCs | 0.0942** | 0.0899** | 0.1010** | 0.1002** | 0.0939** |
| Floors | -1.2622*** | -1.2982*** | -1.2736*** | -1.2755*** | -1.2579*** |
| Garage | 0.5635*** | 0.5814*** | 0.5673*** | 0.5676*** | 0.5651*** |
| Detached Bungalow | 0.1413 | 0.1590 | 0.1603 | 0.1553 | 0.1445 |
| Semi-Detached Bungalow | -0.8198*** | -0.8024*** | -0.7992*** | -0.7915*** | -0.8261*** |
| End Terrace Bungalow | -1.8757** | -1.9263** | -1.9141** | -1.9188** | -1.8741** |
| Terrace Bungalow | -0.6480 | -0.8468 | -0.8481 | -0.7639 | -0.6973 |
| Detached House | 1.1136*** | 1.1641*** | 1.1258*** | 1.1197*** | 1.1104*** |

| | | | | | |
|---|---|---|---|---|---|
| End Terrace House | -0.6464*** | -0.6864*** | -0.6727*** | -0.6663*** | -0.6468*** |
| Terrace House | -0.7060*** | -0.7281*** | -0.7188*** | -0.7177*** | -0.7061*** |
| BG1 | -0.4744 | -0.3362 | -0.4677 | -0.4369 | -0.4590 |
| BG2 | 2.1530*** | 2.2634*** | 2.2012 | 2.1510*** | 2.1540*** |
| BG3 | -0.4121*** | -0.4449*** | -0.4090*** | -0.4071*** | -0.3946*** |
| BG4 | -0.0866 | -0.0442 | -0.0706 | -0.0708 | -0.0777 |
| BG5 | 0.4078 | 0.4558* | 0.3963 | 0.4166 | 0.4207* |
| BG8 | 0.5678*** | 0.6654*** | 0.6096*** | 0.6040*** | 0.5825*** |
| BG9 | 0.8180*** | 0.9129*** | 0.8757*** | 0.8734*** | 0.8208*** |
| BG10 | -2.0383*** | -2.1286*** | -2.0116*** | -2.0402*** | -2.0346*** |
| BG19 | 0.8734*** | 0.9434*** | 0.8838*** | 0.9094*** | 0.8681*** |
| BG20 | -0.7317*** | -0.7202*** | -0.7628*** | -0.7569*** | -0.7334*** |
| BG24 | 1.1242*** | 1.1369*** | 1.1499*** | 1.1413*** | 1.1274*** |
| BG25 | -4.7825*** | -4.8324*** | -4.7345*** | -4.7441*** | -4.7548*** |
| BG30 | -0.9905*** | -1.1046*** | -1.0644*** | -1.0227*** | -0.9928*** |
| BG31 | -0.4484*** | -0.5021*** | -0.4716*** | -0.4620*** | -0.4441*** |
| BG32 | 0.6097*** | 0.6379*** | 0.6081*** | 0.6247*** | 0.6040*** |
| BG35 | 0.9891* | 1.0314* | 1.0783** | 1.0167* | 0.9747* |
| BG36 | -1.8336*** | -1.8833*** | -1.7871*** | -1.7143*** | -1.8108*** |
| ***Neighbourhood Variables*** | | | | | |
| Age60 | 0.0040 | 0.0081** | 0.0067* | 0.0070* | 0.0035 |
| Unemployment | -0.0685*** | -0.0712*** | -0.0700*** | -0.0685*** | -0.0688*** |
| White | 0.0368*** | 0.0388*** | 0.0338*** | 0.0340*** | 0.0367*** |
| Asian | 0.0422*** | 0.0414*** | 0.0413*** | 0.0405*** | 0.0424*** |
| Family with children | 0.0054 | 0.0077** | 0.0062* | 0.0066* | 0.0053 |
| ***Accessibility Variables*** | | | | | |
| Primary Schools | 1.2413*** | 1.2468*** | 1.2373*** | 1.2895*** | 1.2291*** |
| Shops | -0.1109*** | -0.0884*** | -0.0931*** | -0.0913*** | -0.1125*** |
| Rail Station | -0.0082*** | -0.0048** | -0.0053** | -0.0054** | -0.0082*** |
| Park | -0.0007 | 0.0008 | -0.0016 | 0.0002 | -0.0006 |
| University | -0.0197*** | -0.0200*** | -0.0171*** | -0.0180*** | -0.0198*** |
| CBD | 0.0021 | 0.0087 | -0.0006 | 0.0024 | 0.0023 |
| Motorway Junction | 0.0239*** | 0.0205** | 0.0204** | 0.0202** | 0.0218** |
| Airport | -0.0517*** | -0.0506*** | -0.0526*** | -0.0513*** | -0.0522*** |
| Mosque | 0.2790*** | 0.2238*** | 0.2366*** | 0.2443*** | 0.2772*** |
| Industry A | 0.3232*** | 0.3334*** | 0.3617*** | 0.3569*** | 0.3315*** |
| Industry B | -0.0481 | -0.0141 | -0.0014 | -0.0207 | -0.0412 |
| Motorway | 0.0608* | 0.0366 | 0.0877** | 0.1074*** | 0.0459 |
| Road A | -0.1633*** | -0.1909*** | -0.1697*** | -0.1563** | -0.1511** |
| Road B | -0.0744 | -0.0293 | -0.0525 | -0.0328 | -0.0786 |
| Minor Road | -0.8182 | -0.7516 | -0.8945 | -0.7705 | -0.8434 |
| Railway | 0.1199** | 0.0942* | 0.0203 | 0.0288 | 0.1055** |
| ***Environmental Variables*** | | | | | |
| Water View | -0.0001 | 0.0006 | 0.0002 | 0.0000 | 0.0001 |
| Park View | -0.0001 | 0.0000 | 0.0000 | 0.0000 | -0.0001 |
| Road View | 0.0008 | 0.0009 | 0.0003 | 0.0003 | 0.0006 |
| Rail View | -0.0143*** | -0.0156*** | -0.0155*** | -0.0147*** | -0.0146*** |
| Road Noise | -0.0161*** | -0.0178*** | -0.0175*** | -0.0175*** | -0.0162*** |
| Rail Noise | -0.0227 | -0.0143 | -0.0189 | -0.0200 | -0.0223 |

| | | | | | |
|---|---|---|---|---|---|
| Airport Noise | 0.0134 | 0.0225 | 0.0303 | 0.0287 | 0.0132 |
| $NO_2$ | 0.0050*** | 0.0045*** | 0.0054*** | 0.0044*** | 0.0052*** |
| CO | 0.0548 | 0.0671 | 0.0598 | 0.0914* | 0.0513 |
| ***Ward*** | | | | | |
| Aston | -0.5318** | -1.0572*** | 0.0028 | -0.1167 | -0.4632* |
| Bartley Green | -0.5846 | -0.9644** | -0.1574 | -0.2093 | -0.6749* |
| Billesley | 0.1094 | -0.0999 | 0.1554 | 0.2432 | 0.1227 |
| Bournville | 0.3223 | 0.0738 | 0.7887** | 0.8366*** | 0.3335 |
| Brandwood | 0.3165 | 0.0217 | 0.6196** | 0.4791 | 0.3480 |
| Edgbaston | 0.9563*** | 0.6616** | 1.4219*** | 1.3932*** | 0.9003*** |
| Erdington | 1.2074*** | 0.7885*** | 1.2148*** | 1.3742*** | 1.1628*** |
| Fox Hollies | -0.1362 | -0.2594 | 0.1731 | 0.1433 | -0.1205 |
| Hall Green | -0.0050 | -0.2881 | 0.1263 | 0.1760 | 0.0117 |
| Handsworth | -0.0728 | -0.2961 | 0.2421 | 0.2867 | -0.0537 |
| Harborne | 1.3040*** | 1.0313*** | 1.7124*** | 1.8521*** | 1.2723*** |
| Hodge Hill | 1.1528*** | 1.2668*** | 1.2096*** | 1.0884*** | 1.0930*** |
| King's Norton | 0.1738 | -0.1430 | 0.7730** | 0.8336** | 0.1629 |
| Kingsbury | 1.4719*** | 1.0695*** | 1.3390*** | 1.5274*** | 1.4400*** |
| Kingstanding | 0.8487*** | 0.4997* | 0.8960*** | 1.0468*** | 0.7994*** |
| Ladywood | 0.1062 | -0.2681 | 0.3938 | 0.5974* | 0.0348 |
| Longbridge | 0.6759* | 0.2931 | 0.9990*** | 0.9896*** | 0.6663* |
| Moseley | 1.1123*** | 0.7269** | 1.3241*** | 1.2969*** | 1.0906*** |
| Nechells | 0.6942*** | 0.2243 | 0.9141*** | 0.7636*** | 0.8039*** |
| Northfield | -0.0537 | -0.4120 | 0.4433 | 0.5056 | -0.0816 |
| Oscott | 0.3016 | -0.0235 | 0.0959 | 0.3649 | 0.2209 |
| Perry Barr | 0.0295 | -0.5410* | -0.2983 | -0.0130 | -0.0195 |
| Quinton | 0.1400 | -0.1988 | 0.5131 | 0.4923 | 0.0455 |
| Sandwell | -0.1910 | -0.6810** | -0.1921 | 0.0722 | -0.2657 |
| Selly Oak | 0.6760** | 0.2069 | 0.9828*** | 0.9848*** | 0.6692** |
| Shard End | 0.6246** | 0.4953** | 0.6480** | 0.7118*** | 0.5670** |
| Sheldon | -0.1468 | -0.5388*** | -0.0144 | 0.1017 | -0.1016 |
| Small Heath | 0.5584*** | 0.1678 | 0.2893 | 0.4292*** | 0.5523*** |
| Soho | -1.3527*** | -1.9435*** | -1.3557*** | -1.1038*** | -1.4467*** |
| Sparkbrook | -0.2219 | -0.5884** | -0.3549 | -0.0989 | -0.2924 |
| Sparkhill | 0.4947** | -0.0337 | 0.3588 | 0.4605** | 0.4631** |
| Stockland Green | 0.5138** | 0.1418 | 0.7368*** | 0.7664*** | 0.5313** |
| Sutton Four Oaks | 4.1701*** | 3.9595*** | 4.1336*** | 4.3471*** | 4.1768*** |
| Sutton New Hall | 3.2095*** | 2.9980*** | 3.2447*** | 3.4360*** | 3.1881*** |
| Sutton Vesey | 2.4672*** | 2.1593*** | 2.5100*** | 2.6602*** | 2.4202*** |
| Washwood Heath | 0.2566 | 0.0960 | 0.4379** | 0.3429* | 0.3124 |
| Weoley | -0.5291 | -0.9393*** | -0.1055 | -0.0376 | -0.5589* |
| Yardley | 0.2472 | 0.3001* | 0.6436*** | 0.5005*** | 0.2262 |
| ***Landfill Variables*** | | | | | |
| $Active_1$ | -0.2885 | | | | |
| $Historic_{11}$ | -0.1785*** | | | | -0.1757*** |
| $Historic_{12}$ | -0.1800*** | | | | -0.1877*** |
| $Historic_{13}$ | -0.2838*** | | | | -0.2774*** |
| $Historic_{14}$ | 0.0086 | | | | 0.0064 |
| $Active_2$ | | 0.3720** | | | |

| | | | | | |
|---|---|---|---|---|---|
| *Historic* $_{21}$ | | 0.0243 | | | |
| *Historic* $_{22}$ | | -0.2689*** | | | |
| *Historic* $_{23}$ | | -0.0253 | | | |
| *Historic* $_{24}$ | | 0.0081 | | | |
| *Active* $_{3}$ | | | -0.2594*** | | -0.2115** |
| *Historic* $_{31}$ | | | 0.1018*** | | |
| *Historic* $_{32}$ | | | -0.0974*** | | |
| *Historic* $_{33}$ | | | 0.0719*** | | |
| *Historic* $_{34}$ | | | -0.0020 | | |
| *Active* $_{4}$ | | | | -0.0784 | |
| *Historic* $_{41}$ | | | | 0.0610*** | |
| *Historic* $_{42}$ | | | | -0.0188 | |
| *Historic* $_{43}$ | | | | 0.0572*** | |
| *Historic* $_{44}$ | | | | -0.0206 | |
| Constant | 33.4074 | 34.1236 | 33.0268 | 32.4913 | 33.5549 |
| | | | | | |
| θ | 0.1888*** | 0.1916*** | 0.1900*** | 0.1893*** | 0.1887*** |
| Sigma | 1.7771 | 1.8328 | 1.8048 | 1.7925 | 1.7752 |

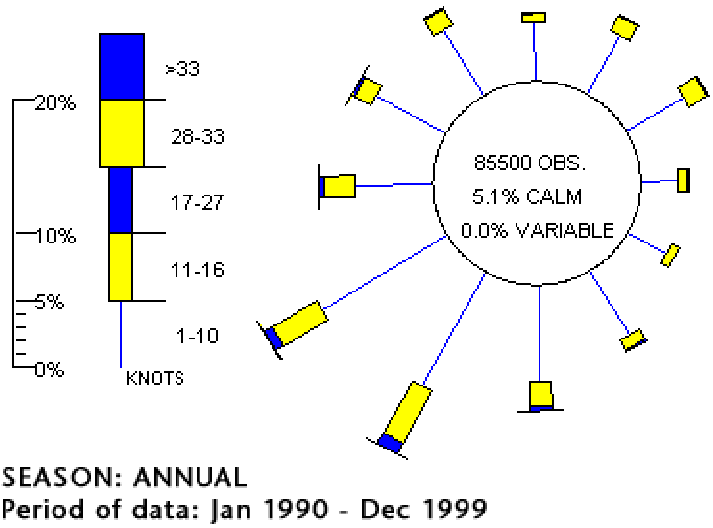
*Notes*: See notes for Table A3.5.1.

**Table A3.5.4: Summary of hypothesis tests for Box-Cox transformations**

| **Model 1** | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| **θ** | 0.1902 | 0.1901 | 0.1896 | 0.1927 | 0.1904 | 0.1909 |
| **θ =-1** | -120526.46 | -120524.08 | -120511.55 | -120514.31 | -120514.62 | -120524.18 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| **θ =0** | -116746.36 | -116742.49 | -116736.67 | -116715.24 | -116731.37 | -116742.48 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| **θ =1** | -119854.26 | -119852.85 | -119845.5 | -119820.6 | -119841.49 | -119843.33 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| **Model 2** | **1** | **2** | **3** | **4** | **5** | |
| **θ** | 0.1888 | 0.1886 | 0.1894 | 0.1906 | 0.1898 | 0.1892 |
| **θ =-1** | -120506.84 | -120505.56 | -120499.31 | -120502.57 | -120502.76 | -120504.31 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| **θ =0** | -116725.41 | -116724.07 | -116711.56 | -116711.96 | -116713.43 | -116721.1 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| **θ =1** | -119851.64 | -119851.5 | -119838.41 | -119828.04 | -119839.19 | -119842.44 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| **Model 3** | **1 km** | **2 km** | **3 km** | **4 km** | **final** | |
| **θ** | 0.1888 | 0.1916 | 0.1900 | 0.1893 | 0.1887 | |
| **θ =-1** | -120492.63 | -120506.28 | -120517.52 | -120518.86 | -120490.66 | |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | |
| **θ =0** | -116706.89 | -116719.25 | -116735.38 | -116741.17 | -116703.97 | |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | |
| **θ =1** | -119837.42 | -119824.88 | -119849.9 | -119855.68 | -119836.01 | |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | |

*Notes*: p-values are in parentheses.

## Appendix 3.6: Wind Direction Distribution




Source: The Met Office, available from http://www.metoffice.gov.uk/climate/uk/mi/print.html

## Appendix 3.7: Local Indicators of Spatial Autocorrelation (LISA)

The local Moran's $I$ statistic (Anselin, 1995) for each observation $i$ is written as:

$$I_i = \frac{(x_i - \mu)}{m_0} \cdot \sum_i w_{ij}(x_i - \mu) \quad \text{with } m_0 = \sum_i (x_i - \mu)^2 / n$$

Where $x_i$ is the observation in location $i$ and $\mu$ is the mean of the observation across locations.

The sum of local statistics is:

$$\sum_i I_i = \frac{1}{m_0} \cdot \sum_i (x_i - \mu) \sum_i w_{ij}(x_j - \mu) = \frac{1}{m_0} \cdot \sum_i \sum_j w_{ij}(x_i - \mu)(x_j - \mu)$$

Thus, the global Moran's $I$ statistic is the proportional to the sum of individual statistics:

$$I = \sum_i I_i / S_0$$

# Chapter 4

# Conclusion

This thesis focuses on two key issues in economics of waste management, particularly in the UK context. The first study is concerned with local variations of recycling performance over time using the concept of environmental convergence which has been widely used to analyse the distribution and dynamics of $CO_2$ emissions. The second study stems from the increasing concern of local communities over the siting and operation of landfill disposal sites, even after their closure.

## 4.1 The First Study

With unprecedented levels of waste generation, there are growing concerns regarding environmental problems associated with landfill disposal. Particularly, the political and social focus on municipal solid waste has been intense due to the scope to improve its recycling/reuse; as well as its complex character and its distribution among many waste generators (EEA Report, 2005).

Traditionally, governments used regulatory standards by setting mandatory targets for recycling or landfill diversion. Such an approach, however, does not provide continuous inducements to change underlying behaviour generating an excessive amount of waste. Therefore, economic instruments are now becoming more widespread forcing waste generators to bear the full costs of their disposal decision (i.e. the polluter pays principle). There are a range of incentive charges in force in the form of taxes or subsidies such as product charges, waste disposal fees and deposit-refund systems.

In response to growing international as well as local pressures on sustainable waste management, the UK government also introduced a set of economic instruments but at the local authority level rather than the individual household. The landfill tax introduced in 1996 is the first market-based system to combat the negative externalities created by disposing of waste into landfill sites. However, the low rate of landfill tax did not significantly increase the price of landfill disposal and still 80% of total municipal waste ended up in landfills in 1999/2000. The real change in the UK waste policy began with the EU Landfill Directive in 1999 under which waste management systems needed to be designed to meet the UK's newfound obligations. First of all, the UK Government set about increasing recycling targets over each five-year period till 2020. To achieve the targets, the Government established various funding schemes and supported the voluntary recycling efforts of businesses. Particularly, we see significant strides towards increasing use of market-based instruments since 2005. The Landfill Tax Escalator and the Landfill Allowance Trading Scheme (LATS) have created strong economic signals to reduce the country's reliance on landfill. Given the recent movements in waste policies, it is worth examining the general as well as local changes in waste management performance, particularly before and after 2005. This is done using three concepts of convergence: sigma convergence, beta convergence and distribution dynamics.

Empirical findings provide strong evidence of convergence in the sense that local authorities with low recycling rates improve their performance faster than those with high rates. Such a catch-up growth both before 2005 is conditional on some socio-demographic factors, particularly population density and unemployment. The period after 2005 also shows the presence of conditional convergence in which population density determine the steady state and the speed of convergence. Nonetheless, the second period has a slower speed of convergence compared to the period before 2005. Overall, this supports the global tendency of convergence across English local authorities over the last decade.

Nonparametric analyses of distribution dynamics reveal useful pictures of distributional characteristics. While the average recycling rates increased over the whole period, the period before 2005 shows that local authorities which initially recycled less than the average made great progress towards the national average rate. On the other hand, the period after 2005 shows that there were two separate clubs of local authorities which converge to some points well below and just above the national average recycling rate. In other words, the gap between groups of low-performing and high-performing authorities has widened over the period after 2005.

This paper also produces some interesting results when spatial dependence in recycling performance is taken into account. Two global spatial autocorrelation tests are carried out to determine if location matters for the distribution of recycling rates across local authorities. The results confirm a significant presence of spatial clustering either high- and low-performing local authorities. Moreover, the inclusion of such spatial interaction in recycling rates confirms the presence of convergence over the whole period while the scale of spatial dependence decreases over the period except one year.

The current findings add to our understanding of how recycling performance has improved over the last decade at the national as well as local authority level. However, one criticism of this study may be related to the data in nature as the quantity of waste and recyclables are measured by weight not by volume. In addition, the study period after 2005 may be too short to conclude a pattern of convergence. In future, updated data for more recent years may improve the analysis of distribution and spatial effects during the period after 2005. Moreover, a separate analysis on each different material may provide more accurate estimates. The study can be improved further by including spatial effects in a nonparametric analysis of distribution dynamics.

## 4.2 The Second Study

Public concerns about health and disamenity impacts often occur among communities near to landfills, even though sites are already closed. Such long-term effects of landfills should be fully taken into account in any appropriate evaluation of the ever-growing costs of waste disposal. This study sets out to evaluate the presence of former landfill sites as a source of disamenity and compare the distinctive features of impacts between active and historical sites. Secondly, this study attempted to fill a gap in the previous literature by examining the multi-site case where residential properties are simultaneously located to many landfill sites.

Empirical findings confirm the negative effects of living near landfill sites. In addition, the following three main findings emerge from the evaluations. Firstly, disamenity impacts remain significant even after site closure even though the effect of historical sites is a lot smaller than that of active sites. Secondly, site-specific characteristics, such as being located downwind of the nearest site, the number of years operated and the type of waste accepted are particularly important elements to determine disamenity impacts of active sites whilst only distance matters for historical sites. Finally, perhaps most importantly, the spatial extent of impacts across active and historical sites is different. The impacts of historical sites and active sites spill over into the surrounding area up to 3 km and 1 km respectively.

Based on these findings, the study takes a further step to deal with spatial dependence in house prices. According to the results of spatial autocorrelation tests, spatial clustering of similarly priced houses is more pronounced than pure randomness. In particular, clustering is significant among low house prices. The inclusion of spatial effects in house prices generally upholds our main findings from the aspatial models regarding the existence of statistically significant effects for historical sites although there are some inconsistent results. For example, the effect of active landfill sites is not much different from that of historical sites. Importantly, the spatial error model appeared to outperform all the other models, which implies the existence of neighbourhood effects captured through spatially correlated nuisance rather than direct price effects.

Finally the study adopts two alternative approaches to explore the issue of housing market segmentation and spatial heterogeneity; a separate regression analysis for each segment divided by property construction type and the use of the locally linear model in which parameter estimates vary over space. The results confirm strong evidence of landfill disamenity impacts and the presence of geographical trends in landfill disamenities and other explanatory variables. With recent advances in non-parametric methods for spatial heterogeneity, more sophisticated techniques such as geographically weighted regression (GWR) could be applied to the property market for more detailed analyses of market segments.

Taken together, this research enhances our understanding of landfill disamenities. However, there are a number of possible future studies which could be undertaken using the Birmingham data. There is scope to improve the quality of the data on wind direction. The current study examined only the effect of wind direction using a variable computed based on only the dominant wind direction over the period 1990-1999. Data on the distribution of wind directions would improve the accuracy of estimates of the disamenity impacts from landfill sites. Wind direction is considered a critical factor influencing the extent of odour and dust experienced by nearby households.

## Reference

EEA Report (2005) *European environment outlook*. European Environment Agency, ISBN 92-9167-769-8.