A spatial analysis of EPCs in The Belfast Metropolitan Area housing market

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Abstract

Energy performance remains a debated topic in real estate, particularly with reference to the capitalisation effect with property value. An emerging corpus of research studies have investigated the relationship between energy performance characteristics and the role of Energy Performance Certificates. Whilst these studies have consistently demonstrated that a pricing effect exists, some recent studies have shown that EPCs are more complex and inconclusive, particularly when accounting for data limitations and changing model specifications. Moreover, a majority of these studies neglect to adequately account for absolute location and therefore, arguably, do not examine the geographic variation between EPCs and property value across the housing market setting. This study presents one of the first spatial analyses of EPCs using transactions for the Belfast Metropolitan Area. In evaluating whether spatial effects exist between EPCs and house prices, a number of spatial tests are performed and a series of models are developed to account for spatial dependency and determine whether there are any spatially correlating effects. The findings indicate that EPCs comprise a partial effect on house prices, and importantly, there are pricing differentials in the spatial variation in EPCs with the pricing effects conforming to both spatial clustering and randomness.

KEY WORDS: housing markets, energy performance, spatial econometrics, house prices, Spatial Lag Model, GWR.

Introduction

In recent years the growing recognition and concern of energy performance, and indeed climatic change, has seen an increasing policy shift and focus on improving the environmental performance of the housing stock (Davis *et al*., 2015). Over the past two decades, the abatement of energy consumption within the built environment has become a core of government policy with increasing emphasis being placed on carbon neutrality within housing stock. Accordingly, government consensus within the European Union (EU) has pushed for legislation and directives targeting energy performance within the housing (market) sector. This drive, originating by the introduction of energy labelling in 2002 is now a mandatory and uniform feature of the housing market across Europe. Since, the evolution and commitment of energy efficiency has witnessed continued traction with further reforms and regulations introduced in the UK to ensure that Energy Performance Certificate are provided to the purchaser or tenant of a dwelling when a building is sold or rented. This has subsequently been further revised, effective April 2018, to include market-based restrictions on the sale and rent of *new* properties on the open market with energy performance ratings below that of category E,[1] and April 2020 for the existing rental housing stock.

It is trite that the introduction of energy labels should be viewed as a step to enhance the transparency of energy consumption in the real estate sector (Brounen and Kok, 2010). Indeed, this point is discussed by Davis *et al*. (2015), who highlight that the underpinning rationale of the EU Directives, through market-based policy instruments such as certification, is to provide accurate and standardized information in order to change consumer behaviour, furnish reliable information on the energy performance and incentivise the improvement of energy efficiency to reap the price premium rather than lose the value of the discount, in other words, see energy-efficient features capitalised into value. As Hinnells and Boradman (2008) denote, the importance of labelling should not be understood in isolation but as an essential ingredient for fostering change and innovation for enhanced energy performance. This has, to an extent, been observed in studies which indicate that the provision of energy

[1] Buildings are graded from A to G based on their energy score ratings (1 to 100).

consumption feedback to private consumers is an effective "nudge" to improve energy efficiency (Ayers *et al*., 2009; Costa *et al*., 2010). Nevertheless, although EPCs appear straightforward conceptually, assessing their impact is more challenging and remains an issue of critical debate. Cerin *et al*. (2014) and Brounen and Kok (2010; 2013) argue that the process of implementation has been gradual, noting that evidence relating to the valuation of energy labels is limited. Fawcett and Boardman (2009) also contend that despite sustained focus on enhancing construction technology to reduce the carbon emissions for new housing stock, the overall market response has been one of lethargy as it does not impact upon the existing stock which represents approximately 85-90% of total market stock.

From a research perspective, the emerging body of empirical study is mixed. A number of studies have identified price premiums associated with improved building energy efficiency (Brounen and Kok, 2011, Hyland *et al*., 2013 and Fuerst *et al*., 2015). In the alternative, other studies have noted more tempered findings (Davis *et al*., 2015; Olaussen *et al*., 2017). However, there is commonality in existing research which has tended to both highlight and lament the unavailability, inaccessibility and deficiencies of data which heightens mis-specification issues, risk of omitted variable bias and potential endogeneity challenges. In this context, studies examining energy performance, akin to other hedonic studies, are largely dependent on, and sensitive to, the level of available data and information relating to variables for model selection. According to Fuerst *et al.* (2015), this is particularly the case if it is suspected that the price impact of an attribute such as energy performance is likely to be small in comparison to other attributes such as location and age of dwelling thus comprising a partial effect. Certainly, the omission of attributes such as quality can be mis-attributed as an energy efficiency price effect. Conversely, the inclusion of variables which are highly correlated and not accounted for correctly can also cloud the 'truer' nature of the pricing effect (Davis *et al*., 2015).

Consequently, the general tenor of previous research recommends the need to enhance model specifications, encompassing more factors across a larger sample size and geographic area to measure the effects of such relationships through time and across space. Indeed, one key dimension which remains under-researched is the locational dynamics of energy performance. Even where existing studies have tended to control for location, this has been included at the regional or delineated census geography level and, at best, post-code level. In a geo-statistical sense, the application, and inclusion of enhanced spatial parameters is to more accurately account for geographically diverse market structures at the neighbourhood or (sub)market level and deal with both measurement and omitted variable bias. Despite this augmentation, absolute location remains an omitted feature within most EPC studies which means they fail to account for spatial heterogeneity and the spatial varying nature of house prices and energy performance (Bloom *et al*., 2011). From a spatial econometrics perspective, the inclusion of delineated (sub) markets merely provides conditional mean estimates for each (sub) market geography, prohibits the varying nature of price determination and does not fully satisfy the assumption of constant error variance across observations, resulting in biased coefficients (Fotheringham *et al*., 2002; McMillen 2010).

Pertinently, these challenges are incumbent of house prices being driven by spatially structured market processes, thereby demonstrating spatial dependence (autocorrelation). It follows that neglecting the inclusion of a spatially lagged dependent variable (spatial autocorrelation) can also lead to biased parameter estimates and the understanding of the relationship between house prices and market characteristics such as EPCs. In light of such statistical concerns, there has been a fundamental uptake in the development of spatial econometrics and modelling over the past 20 years to incorporate realistic assumptions about spatial structures in house price analyses and endeavour to understand the underlying spatial processes. That said, studies investigating energy performance remain largely devoid of a wider spatial understanding in terms of the capitalisation or price premium effects of EPCs. This is an important dimension as across the urban setting there may, or may not, be price premium or capitalisation effects evident which would provide a more localized understanding for policy targeting. To date, the only paper which has examined energy performance using spatial techniques for price estimation (which we are aware of) is the study conducted by Taltavull et al. (2017) who employ a STAR GLS model to evaluate the diffusion effect of house prices spatially by sub-market. As a consequence, it is certainly arguable that location needs to be captured more accurately in order to understand the significance of energy performance within the existing housing stock and housing market context. Indeed, the underpinning economic rationale for analysing the spatial composition of EPCs and their value significant effects pertains to the role of the market adoption and uptake, namely, does the aggregation of older/newer properties in established 'valuable' neighbourhoods reveal a price premium for properties with higher energy performance? or are site positive/negative aspects of 'location' impacting upon EPC value determination. This premise further relates to the reasons why spatial autocorrelation of house prices may be dependent on the level of energy performance, specifically luxury properties in the form of large scale private developments tends to cluster in N.I. - this is particularly the case in the context of modern apartment housing in Belfast city centre, and to a lesser extent, a consequence of spill-over effects of positive externalities within a neighbourhood. If they are spatially aggregated, where do they cluster and is this due to property value, energy performance or both?

This study therefore attempts to address the current knowledge gap by analysing the effects of EPCs on house prices using more advanced spatial modelling techniques to measure the significance of EPCs at the inter and intra-neighbourhood level. Similar to other studies, we develop a series of hedonic based models to investigate the significance of EPCs before turning to examine their 'spatial' composition and relationships. This approach is of significance and value as it helps policy development and discourse into the spatial dynamics of energy performance and offers insights pertaining to energy performance targeting including how government should evaluate the effectiveness of its environmental policies for the existing housing stock.

Literature

Policy Context for Northern Ireland

Energy and climate change policy has received significant high-level support evidenced in the global commitments in the Paris Agreement and the UN Sustainable Development goals, both of which necessitate appropriate national responses aimed at achieving energy efficiency and reducing carbon emissions. In this regard, the UK government were one of the first administrations to legislate on the wider carbon reduction agenda, through the Climate Change Act 2008 (2008 Act), mandating the reduction of carbon emissions by 80% by 2050. Further initiatives are currently being pursued to extend the 2018 MEES (Minimum Energy Efficiency Standard) from EPC band E to EPC band C by 2035 (BEIS, 2017). However, unfortunately at a national level many of these aspirations have failed to be fully implemented or fallen foul of competing government objectives, which in the case of the UK, has seen several green policies rescinded or diluted. For instance, the initial support for implementing zero carbon new buildings and its associated step change revisions to the Building Regulations, as heralded by the *Building a Greener Future* policy consultation (DCLG, 2006), were quickly overturned as a post recessionary measure to avoid undue hardship on property developers. Further, financial support through the Green Deal and incentives for renewable energy, as well as the recognised assessment tool (Code for Sustainable Homes), have also been phased out in what can only be described as a conflicting green policy agenda. Recently, as one of the last acts of her administration, then Prime Minister Teresa May attempted to redress this balance by advocating for a renewed target of net-zero greenhouse gas emissions by 2050. This commitment moves substantially beyond the initial 80% reduction originally legislated under the 2008 Act, and given previous failures, the jury is out on whether this will galvanise the green movement.

In the Northern Ireland context, similar mixed messages are evident. Whilst the geographical extent of the Energy Act 2008 technically extends to Northern Ireland, there are a number of provisions which do not. Nonetheless, the last Programme for Government (2011-2015), prior to the Stormont Executive's untimely cessation, contained at 35% reduction target by 2025. Further, in the Strategy Energy Framework 2010-2020 , the jurisdiction has a 40% renewable energy target by 2020 which it is on target to meet. In 2010, Northern Ireland also implemented a rates relief scheme for low carbon homes, albeit this policy was later rescinded due to lack of take-up prior to the market for energy efficient homes being fully established. Pertinently, there are no current proposals on implementing

MEES on sales or lettings although this is likely to be part of any renewed draft climate change bill if or when the NI Executive gets back in session. Further incentives on renewable energy (NI Renewable Obligation Certificates) and renewable heat (RHI) have been phased out in relation to the former and for latter shamefully abolished in the wider 'cash for ash' controversy. Localised incentives to improve the energy efficiency of homes have been targeted at lower income households through the NI Sustainable Energy Programme (NISEP) funded by the major energy suppliers and delivered via small grants towards mainly heating and insulation measures. Overall, the lack of political leadership, legislation provision and policy revisions places Northern Ireland's energy policy in a period of stagnation and ambivalence.

A price premium or capitalisation effect?

Studies investigating the value of energy performance in the residential sector have been in existence since the 1980s with the pioneering study by Halvorsen and Pollakowski (1981) examining the relationship between heating type in properties in Seattle, USA finding a marginal pricing effect between heating types, with Gilmer (1989) and Dinan and Miranowski (1989) also showing positive impacts of energy labels and energy-efficiency improvements. Since then, the more wholesale introduction of energy labelling has seen a flurry of activity within academic research.

A seminal paper undertaken for the Australian Bureau of Statistics (Berry *et al.,* 2008), examining over 5,000 transactions in the Australian Capital Territory investigated whether price premiums related to increased Energy Efficiency Ratings (EER). Their results showed increased price effects (1.2%) with every unitary increase in EERs. Further utilizing a pooled sample against a zero base, the authors established premiums ranging from 1.6% (EER 1), to 6.1% (EER 5) reflecting increased premiums with higher EERs, albeit a marginal decline or 'ceiling' effect for the highest EER dwellings. More recently, Fuerst and Warren-Myers (2018) further investigated whether high levels of non-disclosure leads to adverse market outcomes – adverse selection of economic risks – and tested if energy efficiency ratings (EERs) are reflected in both housing sales prices and rents in the Australian Capital Territory. Utilising both sale and lease transactions (2011–2016) they applied a hedonic framework showing that both the reported energy-efficiency levels and other sustainability-related characteristics that are not part of the formal rating assessment influence the pricing of both sales and rental transactions. Interestingly, they illustrate that characteristics such as heating and cooling systems and the presence of solar power generators are significantly reflected in rents and sales prices, which they pin to the reduction of expected utility costs. In terms of spatial dynamics, their analysis also reveals that socio-economically disadvantaged areas suffer from disproportionately higher levels of EER non-disclosure, potentially constituting a 'double disadvantage' of non-disclosure and low–energy efficiency dwelling stock. Warren-Myers *et al.* (2018) in a more behavioural approach, and using a pilot case study, investigated consumers' awareness, motivations and experiences for purchasing dwellings that are situated in a sustainability-based certified development. Their findings infer that the sustainable rating systems are not having the desired influence as originally envisaged which the authors conclude demonstrates that regardless of their concern for environmental issues, consumers have both low awareness and trust in the ratings.

From the US perspective, Bloom *et al.* (2011) conducted hedonic analysis using a small sample of 300 sales, finding a premium effect of $9 per square foot for Energy Star labelled dwellings compared to unlabelled dwellings. In a comparable study undertaken by Kahn and Kok (2014) which also used a hedonic pricing approach, analysed single-family home sales for California between 2007 and 2012 using a sample of matched dwellings. They found a 2% premium for green labelled dwellings relative to comparable non-labelled properties. Interestingly, the authors present evidence of spatial variation within this capitalisation effect which they attribute to local climatic conditions and environmental ideology which they suggest explains the variation in green premiums across market geography. Their descriptive analysis illustrated clustering of green rated housing with income profile and hotter metropolitan areas inferring that there is a spatial dynamic to energy performance. More recent literature by Aroul and Rodriguez (2017) extended the insights into green premiums by examining the temporal variations in green premiums to measure increasing consumer demand and awareness of the economic benefits as well as non-financial benefits of energy efficiency. The authors make a compelling argument that appraisers should not generalize findings for one market across markets that have different climates or attitudes regarding green amenities. Indeed, they stress that lower income individuals can experience higher financial benefits, relative to their incomes, from the savings stemming from green amenities. However, the authors also infer that individuals in lower income areas may lack the financial capacity to take advantage of the benefits available from green amenities. They recommend that policymakers should develop programmes that help lower income individuals gain access to the growing benefits of green amenities. Bruegge, *et al.* (2016) also examined whether the housing market values energy efficient homes using the "Energy Star" certification which is a mechanism instilled to incentivize home builders to 'build green'. Adopting a Marginal Willingness-to-pay (MWTP) approach for Energy Star residences in Gainesville, Florida between 1997 and 2009, they use a hedonic framework to estimate single-family residential property sales, finding that homeowners are willing to pay a premium for new Energy Star homes, but that these premiums fade rapidly in the resale market.

The study conducted by Brounen and Kok (2011) was one of the seminal studies in the European context scrutinising the economics of energy labels within the Dutch housing market for 2008-2009. Their study examined two fundamental aspects of EPCs, namely, the adoption of EPCs within the Dutch housing market, and secondly, the market implications of energy labelling. Using 177,000 transactions the authors found geographic variation, based on economic and political behaviour. Interestingly, the authors highlight that neighbourhood characteristics comprised a distinct influence on the propensity to adopt a labelling which were commonly located (clustered) in neighbourhoods typical of higher density, particular property type, lower incomes and political priority towards environmental issues. Pertinently, the authors attributed the regional variation in energy labelling adoption to market competitiveness in a local housing market context and labelling as a (market) mechanism to increase transparency. Whilst showing clusters of adoption, the authors conceded that due to initial transparency concerns, this inhibited wider market uptake resulting in energy labelling becoming non-random. In addition, with regards to market signalling and capitalisation effects, the authors, based on a sample of 33,482 residential sale prices for dwellings with (voluntary) EPC ratings, used the Heckman two-step method to find that homes with a green label sell at a premium of 3.6% relative to otherwise comparable dwellings with non-green labels. This transaction premium they found varies from 10% for A-rated properties to a discount of 5% for G-rated properties – benchmarked against D-rated dwellings. Whilst controlling for a range of neighbourhood characteristics (housing density, time on market and monthly household income), these are at the post-code level or provincial level and presented as fixed effects.

In updated studies, Murphy (2014) draws on data from ex-ante and ex-post assessments of EPCs to investigate the influence of the EPCs on private purchasers in the Netherlands. The results revealed EPCs were found to have a weak influence, especially for pre-purchase. Chegut *et al.* (2016) also analysed energy efficiency – concentrating on the affordable housing sector in the Netherlands. Analysing the value effects of energy efficiency in the affordable housing market using a sample of 17,835 homes sold by Dutch affordable housing institutions over the period 2008-2013, they utilise EPCs to determine the value of energy efficiency in these transactions. They reveal that dwellings with high energy efficiency sell for 2.0–6.3% more compared to otherwise similar dwellings with low energy efficiency.

In a more wide-scale report undertaken by the European Commission (2013) several European city markets were evaluated for the effects of EPCs on pricing and rents. The results showed consistent findings of a premium effect, albeit based on different sample sizes, model specifications and attributes. In Austria and specifically the Greater Vienna region the study revealed an 8% premium based on 2,246 sale transactions, with a 4% premium observed for rental pricing (1,077observations). Within the French context, the two cities of Marseilles and Lille were examined respectively using samples of 1,263 and 1,915 transactions. The results showed an approximate 4% increase in the unitary change in EPC rating. Finally in the Irish context, circa 26,500 rent prices and 11,000 sales prices were scrutinized – albeit for listed prices only. The findings showed a 2.8% increase per unit change in EPC rating for market pricing and a 1.4% increase in rental prices. Significantly, all the case studies within the sample neglected to adequately control for location characteristics.

From a rental market perspective, Feige *et al.* (2013) examined a sample of 2,453 rental prices for apartments in Switzerland using a composite sustainability metric based on 36 input characteristics to obtain a sustainability score for each dwelling. Their findings illustrated that various aspects of the sustainability features demonstrated positive, negative or no effects. Notably, the authors found that energy performance commands a negative relationship with rental prices which they attribute to lease structures which price in energy costs for less energy efficient buildings. Notably, the authors do not account for spatial variation. In a similar fashion, Kholodiliin and Michelsen (2014) evaluated the residential rental market in Berlin finding that energy savings appear capitalised into prices and rent price movements. This was also subject to a study conducted by Cajias and Pizazolo (2013) who in their more investment orientated performance analysis of residential buildings using a sample of 2,530 observations between 2008 and 2010, show that a one percent increase in energy efficiency comprises a 0.08% uplift in rental returns and 0.45% increase in market value illustrating price and rent premiums for properties in EPC bands B, C, and D relative to E, F, and G banded property. Furthermore, Amecke (2012), similar to Brounen and Kok (2011), evaluated the adoption and impact of EPCs using a survey examining private purchasing decisions for 1,239 existing dwellings in Germany. Analysing the extent to which EPCs have helped owner-occupied dwellings to incorporate energy efficiency in their purchasing decisions, the results suggest that the effectiveness of EPCs is marginal. The authors note that primarily the certificates are not helpful for understanding the financial implications of energy efficiency, although they do acknowledge that EPCs performs well with regard to general awareness.

In a Northern Irish context, studies have examined the value enhancing effects of EPCs. Davis *et al.* (2015), investigated the relationship between energy performance certificates and property prices in the Belfast housing market. Using a hedonic pricing specification, they indicated a trivial but positive relationship between superior energy performance and higher selling prices (0.4%). Nonetheless, the findings point towards strong preference, demand tastes and a complex intra-relationship between EPCs and their capitalisation into property value. Moreover, the authors indicated that the EPC-pricing relationship is masked and confused by the heterogeneity of the housing stock. Analogous with other studies, the authors note that data deficiencies and a lack of incorporating price determining variables (missing determinants) such as heating type, glazing type and local government delineated boundary locational dummies introduces omitted variable bias and endogeneity problems within the model structure and limits a more spatial observation of the pricing effects.

In a slightly different perspective, Davis *et al.* (2017) further examined the role of EPCs in the context of property taxation within Northern Ireland. Investigating the extent to which EPCs can be modelled using a limited set of property characteristics gathered for property valuation purposes, they found that much of the explanatory power of EPCs scores are largely driven by basic property tax related characteristics (type and age) often already held by property tax jurisdictions. Of significance, the findings highlighted that superior energy performance is to a certain degree spatially aggregated in urban areas and that there is a potential urban-rural divide when considering the role of energy performance. The authors do note however that the modelling illustrated that the more granular the analysis, the more complex the spatial depiction of energy performance across the entirety of Northern Ireland and that there is a spatial aggregation effect evident warranting further spatial analysis of energy performance within the housing stock.

In keeping with the Irish context, Hyland *et al.* (2013) analysed the effect of energy efficiency ratings on the sale and rental prices of dwellings in the Republic of Ireland. Using the Heckman selection technique, the authors show that energy efficiency has a positive effect on both the sales and rental prices of properties, and that the effect is significantly stronger in the sales segment of the property market. Specifically, they found asking price premiums relative to D-rated dwellings for A (9%), B (5%) and C (1.7%). There was no significant discount for E-rated dwellings and a discount of approximately 11% for F/G. Rental premiums were 1.8% for A and B rated dwellings compared to D and no significant price effect on C-rated dwellings. There were rental discounts for E (1.9%) and F/G (3.2%) rated dwellings. The analysis does not appear to control for age of buildings and as a result there may be a risk of misattributing age effects to energy efficiency effects. Notably in their analysis they use 35 regional dummy variables to control for location and a rural classification where necessary. Building upon this study, Stanley *et al.* (2016) introduced the age of building and location specific submarket geography for dwellings in the Dublin housing market between 2009 and 2014. The results suggest that energy efficiency has a significant, positive relationship with list price, namely, a 1-point improvement in the 15-point scale from G to A1 yields a list price increase of 1%.

In the wider UK context, for the English housing market, Fuerst *et al.* (2015) utilised a large sample of 325,950 observations to measure EPC effects on prices using a two stage estimation procedure to remove unobserved variables in the model. The authors discovered significant positive price premiums for dwellings with EPC ratings of A/B (5%) or C (1.8%) compared to dwellings rated D. For dwellings rated E and F statistically significant discounts were estimated, −0.7% and −0.9% respectively. Dwellings rated G sold for approximately 6% less. Turning to price growth, the findings were less pronounced revealing diminutive (0.1%) increases in house price per square metre for every unit increase in energy efficiency (relative to band D houses). Their findings however illustrated that two stage estimations revealed no sizable changes in premiums and results are more inconclusive due to marginal diminishing returns for price per square metre growth for A/B rated houses (relative to D rated houses). The results also identified differential effects by property type with a superior premium effect evidenced in smaller sized properties (terrace houses and flats) compared to large sized properties (detached and semi-detached houses). They also observed that the level of premium varied across regions using a regional level location dummy.

In a different study for the Welsh housing market, Fuerst *et al.* (2016a) investigates the effect of Energy Performance Certificate (EPC) ratings on residential prices. Drawing on a sample of approximately 192,000 transactions, the capitalisation of energy efficiency ratings into house prices is investigated using two approaches. The first adopts a cross-sectional framework to investigate the effect of EPC rating on price. The second approach applies a repeat-sales methodology to investigate the impact of EPC rating on house price appreciation. Statistically significant positive price premiums are estimated for dwellings in EPC bands A/B (12.8%) and C (3.5%) compared to houses in band D. For dwellings in band E (−3.6%) and F (−6.5%) there are statistically significant discounts. Such effects may not be the result of energy performance alone. In addition to energy cost differences, the price effect may be due to additional benefits of energy efficient features. An analysis of the private rental segment reveals that, in contrast to the general market, low-EPC rated dwellings were not traded at a significant discount. This suggests different implicit prices of potential energy savings for landlords and owner-occupiers.

In the Scottish housing market, Liu *et al.* (2018) in a WTP framework for the private rented sector for Aberdeen and its surrounding hinterland, used rental data between Q3 2013 and Q2 2017 to analyse rental premiums for energy efficient rental properties. Their results revealed between a 2% and 11% premium associated with more energy efficient dwellings. The authors found however that such premiums were significantly reduced during the economic recession, suggesting that tenants' WTP for energy efficiency varies under different economic conditions.

From the Scandinavian viewpoint, Högberg (2013) assessed the impact of energy performance on single-family home selling prices in Sweden using 1,073 observations within a hedonic framework. Specifically, the study tested cost-effective energy efficiency measures to establish whether improvement recommendations enhance pricing effects. The results suggest that superior energy performance has a premium effect. Cerin *et al.* (2014), also investigate the role of mandatory energy performance certificates after the implementation of the EU directives. Analysing transactional data between 2009-2010 the authors found that energy performance is associated with transaction price for labelling and price premiums for energy performance within housing segments built before 1960 and those with a lower transaction price per square metre. Their findings infer that the property market values energy performance, and that particular housing segments need policy targeting and support. With regards to Finland, Fuerst *et al.* (2016b) studied the impacts of energy efficiency for the apartment sector employing 6,194 observations transacted between the years 2009 and 2012. The analysis indicated a significant price premium for the top three highest EPC categories (A, B, and C) relative to D banded property and no premiums noticed for bands lower than D (E, F, and G). In a similar vein, Olaussen *et al.* (2017) exploring EPCs and primarily their effect pre and post EPC introduction into the Norwegian housing market, show that a price premium associated with energy labels is inconclusive and partly contradictory. Analysing data from the Norwegian housing market, they reproduce the positive price premium effect found in earlier studies, however, calibrate these to uncover no evidence of a price premium and no effect of the energy label itself.

From a more Southern European perspective, there appears to be less impetus and implementation for energy labelling which appears somewhat lacking. Fregonara *et al.* (2014) evaluated the impact of EPCs on the listing price market within the Italian housing market. Using a sample of 577 list price values for Turin over 2012, the authors observed a discount for apartment units with F label (relative to B label) and F/G labels (relative to B/C labels) though conclude overall that there is a weak relationship between list price and high energy levels citing energy not to be a primary consideration for potential buyers. Interestingly, the authors showed no dependence between qualitative variables included in the study for location, buildings quality and apartment condition. Similarly, for Spain, de Ayala et al. (2016) compared premiums across different groups of energy labels. Acknowledging the lack of market data, they use a sample of 1,507 randomly selected properties across Spain based on household survey data at the regional level from 2013. Using a hedonic approach, the authors found that more energy efficient dwellings display a price premium between 5.4% and 9.8%. However, they acknowledge a lack of attribute control variables which reduce explanation and introduce bias.

For Eastern Europe, Taltavull et al. (2017) investigate the impact of energy performance on transaction prices for the apartment sector in Bucharest. Estimating the green premium effect of retrofitted apartments, they developed a geo-referenced transaction database including information on whether the property had been retrofitted. Utilising two modelling approaches they firstly estimated the price incentive of a green building controlling for area, with the second approach the specification of a STAR GLS model in order to evaluate the spatial diffusion effect of house prices by sub-market and assessment upon the pricing effect of green characteristics. Their findings suggest a green premium in two areas between 2.2 per cent and 6.5 per cent with further Spatial diffusion effects revealed to contribute positively to house prices, nonetheless highlighting that the unobserved spatial component reduces this effect.

The existing literature clearly highlights the challenges embedded in undertaking analysis into energy performance and establishing whether it comprises a capitalising effect upon property value. By-and-large, a vast array of these contemporary studies, both hedonic and survey based, deem that increased energy efficiency is rewarded with higher transaction, listed or rental pricing, a number of which comprise similar socio-economic and legal frameworks within the UK providing context for this study region. The literature does however show a wide variation in the level of the price effect, which is arguably conditional on the granularity of the data (or lack thereof) and sales price information used for controlling for endogeneity issues. Indeed, this appears to be a secular issue. A number of the existing studies have attempted to incorporate a wide range of quality controls of the dwelling attributes, though less so for location. Indeed, key findings such as that of Aroul and Rodriguez (2017) have suggested that when analysing energy performance we should not generalize findings for one market across markets that have different climates or attitudes regarding green amenities suggesting that it remains very much a behavioural issue which can imply that there is limited uptake across housing markets in an aggregation sense. Meanwhile, other studies have alluded to role of spatial dynamics and differential effects based on socio-economic standing. The majority of studies have employed delineated market boundaries at various spatial levels with the most granular being the use of post-code level delineation as fixed (interaction term) effects and it is notable that the emerging empirical research is gravitating towards the recognition of a more granular spatial comprehension of EPC's. Whilst positive, a fundamental issue relates to the conditional mean estimates these provide which overlook the spatial varying nature of property prices and indeed EPCs. One important aspect, as evidenced within the literature, is the lack of absolute location for providing a more geographically delineated position on the role of energy performance in a wider market context. This paper is positioned in this debate and seeks to add to the literature base by identifying the extent to which energy labelling is associated with location and how this impacts upon the pricing effect.

Data and Modelling

The data is obtained from the University of Ulster House Price Index (UUHPI) for the period Q3, 2013 to Q3, 2014, representing a cross-section of the Belfast Metropolitan Area (BMA)[2]. The UUHPI is an established property market index dating back to 1984 which is based on a robust sample of achieved price transactions obtained from estate agents on a quarterly basis. This sample encompasses circa 40% of all recorded property transactions across Northern Ireland on a quarterly basis and is verified and validated using robust data checks and testing procedures. This initial database of 4,096 records was purged based on removal of duplicate entries, missing observations and erroneous data entry[3]. This was subsequently merged with an asking price datafile obtained from the UU Asking Price Index[4] comprising addresses and EPC data. An address matching exercise was performed to align the EPC scores with the house price transaction records. A spatial database was further constructed by incorporating *X,Y* coordinates using Geographical Information Software (GIS), leaving 1,478 observations for analysis (Figure 1). All variables, where appropriate, are transformed into binary state. This process is undertaken to indicate the absence or presence of a categorical effect that may be expected to shift the outcome (Kleinbaum *et al*., 1988) as within hedonic analysis a dummy explanatory variable with a value of zero will comprise no influence on the dependent variable, whilst a value of one results in the coefficient influencing the intercept. The data was subsequently exported into the statistical packages EViews, *R* and SAM[5] to permit geo-statistical analysis.

<<<Insert Figure 1 Property EPC data and scores>>>

A description of the data variables employed within the study can be evidenced in Table 1. For measuring the impact of EPCs, we primarily use the EPC score, however we also do test the effects of banded EPC scores within the initial OLS and GWR model frameworks[6]. The nuance in the analysis is the incorporation and use of the EPC score within this research for two reasons. Firstly, given that property price is a continuous variable and that the EPC rating is provided as a continuous score, this provides a more deterministic relationship which is more natural for comparison spatially. Moreover, as we are investigating the spatial variation of EPC performance, it is more efficient to utilise the continuous scale as this permits model estimates of the EPC score to be created and spatially referenced to permit a more granular depiction. In this regard, for spatial analysis purposes, the transformation of a continuous EPC score to a categorical or binary EPC band evades the use of price-point information needed for spatial econometric techniques. Secondly, EPC banding can be an arbitrary measure as each classification is based upon a range (e.g. 59-68 equates to D; 69-80 equals C). This calls into question how they are measured for pricing relationships as a one-point transition can result in a different banding classification – a discontinuity boundary effect - and evidence of an artificial price premium effect.

<<< **Table 1 Variable Descriptions>>>**

The data does contain a number of limitations, primarily missing determinants of energy efficient features and the condition of the property which were not included in the data sample or available for any potential data matching exercise. Whilst we acknowledge that particular property characteristics such as glazing type are missing, we have attempted to include the major attribute information which impact upon pricing and EPC score. This lack of granularity can impact upon analysing model

[2]The BMA is the largest urban area in Northern Ireland spanning $960km^2$ comprising six delineated geographic District Council Areas.
[3]The data collection process encompasses the triangulation of three different data sources, of which some can record the same transaction. Therefore a robust validation process is undertaken to ensure validity and reliability and the removal of duplicates.
[4]This Index is based on Asking (List) prices collected from property agents over the year period and manually matched by address. This Index covers circa 45% of all listed properties across the NI jurisdiction. This was cross-referenced with the Landmark register.
[5]See: Rangel, T. F., Diniz-Filho, J. A. F., & Bini, L. M. (2010). SAM: a comprehensive application for spatial analysis in macroecology. *Ecography*, *33*(1), 46-50.
[6]We test EPC banding for statistical significance within the initial OLS framework.

significant determinants, however, it can also introduce issues of multicollinearity. In addition, more granular data characteristics such as replacement windows are arguably implicitly priced into both the property value and EPC score estimates respectively through their original valuations and energy performance inspections.

In terms of sample representativeness, and to ensure reliability of the findings, the sample size across the property attributes were investigated in order to confirm representation within the sales transaction dataset (Table 2). As evidenced, semi-detached housing displays the highest volume of sale transactions constituting 35.72% of the sample, with both detached and terrace (townhouse) property types comprising just over a quarter of the sales each representing 27.60%. Apartments constitute the lowest market share representing 9.10% of the sales transactions. In terms of property age, newer built properties are the most representative revealing 29.91% of the sample data to comprise properties constructed Post-1980. Early-modern (post 1960s) properties account for 25.71% of the sample with both inter-war and post-war period housing equating to 17.93% and 17.66% respectively. With regards to heating type, properties with oil heating equates to 61.91% of the sample with gas heating accounting for 35.39%. Both electric heating and traditional solid fuel (coal; wood) comprise a nominal 1.96% and 0.74% of the sample.

<<<Table 2 Sample representativeness and adequacy>>>

Descriptive analysis

A summary of the descriptive statistics for the data is presented in Table 3. The sample mean property price is £164,182 which reveals a high dispersion and positive skew (Figure 1 a). The average floor size is $122m^2$, again displaying a high variance and positive skewness (Figure 1 b), with the average EPC score of 54.19 which falls marginally below the EPC category D, and in line with the wider UK average residential EPC band rated D[7]. Interestingly, the standard deviation for the EPC score shows that 68.4% of properties reside between an EPC score of 69 and 39 and that the distribution of EPC scores is relatively normal (Figure 1 d) only being marginally negatively skewed (-0.24).

<<<Table 3 Descriptive Statistics>>>

Further disaggregation of the sample data exhibits marginal variation across property type and age profiles with respect to EPCs (Table 4). The average EPC score for apartments (56.03) is the highest in the sample, nonetheless, the remaining property types all show an average EPC score within a 1.5% range (53.26-54.54). This is also evident for range and standard deviation across property type exhibiting the different types to all have very similar distribution characteristics. When considering the age of the properties, there is a low variation across each respective age band in terms of EPC performance (52.72 – 55.15). Surprisingly, the Inter War period housing has the highest EPC score within the sample, perhaps reflective of refurbishment and retrofitting, followed by the new build and post-1980 period properties.

<<<Table 4 Descriptive statistics by property type and age>>>

Data exploration and identification of spatial structures

As with any hedonic based study (parametric and non-parametric), model functional form is an essential selection process to ensure model reliability and validity of parameter estimations. In this regard, initial inspection of the data reveals asymmetry within the sales price dependent variable, thus illustrating potential for mis-specification. As a consequence, the sales price variable is transformed into its

[7] See:https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/729052/EPB_Cert_Statistics_Release_-_Qtr_2_2018_final.pdf

logarithmic state in order to standardise to a normal distribution to comply with standard statistical assumptions.

Model selection and multi-model inference

To ensure model parsimony and appropriate model selection, initial testing of structural (physical) parameter selection was undertaken to reduce model complexity without reducing model predictability. This model selection procedure, based on minimising the Akaike Information Criteria(c), ensures retention of the highest level of explanation as depicted by the Adjusted R^2, is undertaken to reduce the model form and examine the most parsimonious spatial model and remove unwanted influential variables and multicollinearity[8]. The AIC(c) statistic is based on the maximum likelihood of estimating parameters,β_i, where the probability of the observed data would be as large as possible (Burnham and Anderson, 2002), computed as its small sample corrected version as this is asymptotic to the standard version[9]. Within this research, this process is based on 13 variables selected culminating in 8,191 models tested (Table 5). The results of the selection procedure filtered by the AIC revealed that the most parsimonious model form excluded electric and solid heating types, and Post-War house type.

<<<Table 5 OLS Model Selection procedure sorted by Akaike Information Criterion (AICc)>>>

Spatial Structure Analysis

Given that the emphasis of this paper is to understanding the spatial structure and relationships between property pricing and energy performance, the preliminary step in all spatial analysis, as in any other statistical procedure, is to undertake exploratory data analysis (EDA) to uncover (usually) hidden patterns in datasets in order to quantify relationships between variables (values) and further examining these across spatial units[10]. In this regard, this paper explores the spatial dynamics of the data using a series of spatially based data approaches for further model testing. One of the most frequently discussed issues within property literature pertains to spatial autocorrelation which is the inflation of Type *I* errors in the significance tests of correlation and regression analyses resulting in errors in statistical inference and the independence of observations and heteroskedastic error terms (LeSage and Pace, 2009). This indicates that if two (or more) variables are strongly spatially autocorrelated i.e. that spatial units close in geographical space are partially redundant with respect to the information they provide about the relationships between variables. In other words, in the presence of spatial autocorrelation, the number of degrees of freedom is overestimated, and consequently, confidence intervals are much narrower resulting in errors in statistical inference under a null hypothesis due to the confounding effects of space. In order to test the spatial structure of the data, a number of tests are undertaken based on the *X, Y* coordinates with pricing and EPC response variables selected[11].

Accordingly, spatial correlation[12] were undertaken to examine the extent of spatial autocorrelation across the distance units. The results showed the spatial patterns to comprise both positive and negative autocorrelation within the short- and long-term distance classes indicative of pockets of spatial clustering and dispersion symbolic of the heterogeneous nature of housing markets. In light of the presence of spatial autocorrelation, the correlation coefficient was tested for the number of degrees of

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[8] This procedure estimates the relative quality of the models for the given set of data, relative to each of the other models premised on the relative information lost by a given model: the less information a model loses, the higher the quality of that model. This therefore estimates the trade-off between the 'goodness of fit' of the model and the simplicity of the model.
[9] See De Smith et al. (2007) for a full discussion.
[10] see Rossi *et al*. (1992) for a discussion of EDA within the framework of spatial analysis.
[11] Geographic distances determined using a symmetric distance matrix (Upper right distance matrix) based on a default number and equal distance classes with significance tested using 199 permutations There are 21 Distance classes. These are not presented due to space limitations. All Distance classes are available upon request.
[12] Using a truncated distance matrix (truncated to 13,367.216).

freedom as developed by Clifford *et al*. (1989)[13]. The results show sale price and floor area (property size) to be highly correlated and significant when corrected for the degrees of freedom in a spatial context – an a priori expectation. Interestingly, property size (Floor Area) and EPC scores display a low level of explanation (4.6%) and is only statistically significant at the 10% level, with sale price also exhibiting a low correlation with EPCs 5.7%, significant at the 5% level. This initial testing therefore provides indication that there are instances of spatial aggregation and dissimilarity in terms of pricing and EPCs and despite this that the level of association is low. These findings are confirmed through the application of both the Moran's I and Local Moran's I (L.I.S.A) tests which evaluate whether the pattern expressed is clustered, dispersed, or random[14i]. The findings present a relatively complex geographic market structure (clustering and randomness) for the house price and EPC parameters. Therefore, we adopt a number of different modelling approaches to scrutinise the relationships.

Model selection

As the focus of this research, similar to other studies is to examine whether EPCs have a capitalising effect on house prices spatially, or if EPCs are reflected in house prices either in a positive or negative sense uniformly across the housing market, we build a series of traditional hedonic models and further this through specification of spatial modelling approaches for two reasons. Firstly, whilst specification of hedonic models have improved through the implementation of spatial dummy variables to account for neighbourhood characteristics and proximity, such variables are considered to not fully satisfy the assumption of constant error variance across observations, and ultimately leave coefficients biased (Khalid, 2015). Moreover, this is generally premised upon geographic (governmental) delineated boundaries which restricts the ability to accurately assess the varying nature of the market structure. Secondly, from a theoretical spatial econometric stance, neglecting the inclusion of a spatially lagged dependent variable (spatial autocorrelation) can lead to biased parameter estimates as a result of spatial dependence which can be defined as the interdependence among house prices (and EPCs) due to their relative geographic locations from each other. Accordingly, to account for spatial dependence and heterogeneity we adopt a Spatial Expansion, Geographically Weighted Regression (GWR) and Spatial Lag Model (SLM) to explicitly account for spatial heterogeneity using spatially varying coefficients and control for both indirect and direct effects[15].

Modelling Specifications

OLS (Spatial Regime) Model

Hedonic price modelling is the prominent approach for determining the marginal effects of property characteristics on value. As introduced by Rosen (1974) it is based on the assumption that parameters have a cumulative effect on the price of a good, thus the basic house price model is the functional relationship between the price (P) of a heterogeneous good and its quality characteristics represented

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[13] For a full discussion see: Legendre, P. (1993) Spatial autocorrelation: trouble or new paradigm? Ecology, 74, 1659-1673; Legendre, P., Dale, M.R.T., Fortin, M.J., Gurevitch, J., Hohn, M. & Myers, D. (2002) The consequences of spatial structure for the design and analysis of ecological field surveys. Ecography, 25, 601-615

[14] These are the most commonly used statistic for autocorrelation analyses in spatial studies (See Fotheringtham et al., 1998; Anselin, 1992; Tiefelsdorf, 2000) as they calculate the Moran's I Index value and both a z-score and *p*-value to evaluate the significance of that Index. P-values are numerical approximations of the area under the curve for a known distribution, limited by the test statistic.

[15] We consider both ways to incorporate spatial effects into a regression model: the spatial-lag model and the spatial error model. These two model specifications are closely related mathematically, but each has a different economic interpretation. The SLM is preferred (to the SEM) as we have identified that there is structural spatial interaction, as in the spatial reaction function and we are interested in measuring the ''true'' effect of the explanatory variables, after the spatial autocorrelation has been removed.

by a vector X of attributes and β pertaining to the vector of coefficients estimated for the characteristics. The hedonic equation takes the form:

$$y = X\beta + \varepsilon \tag{1}$$

The hedonic approach is nonetheless open to interpretation given that the price function is an envelope of bid functions which can give rise to mis-specification challenges. To combat this, we also test the functional form of the hedonic equation using the semi-logarithmic equation to ensure reliability of results and, as previously indicated, account for the skewness within the sample price data. Indeed, the semi-log linear fit is applied within the modelling frameworks due to computational efficiency and interpretability which provides useful interpretations of the independent variable coefficients in terms of their elasticity in respect to the dependent variable. The semi-log specification is as follows:

$$(Ln)y = X\beta + \varepsilon \tag{2}$$

Where; LnY is the dependent variable (log of sale price), X are the independent variables; β are parameters to be estimated; with ε the error term. The percent effect is calculated using Halvorsen and Palmquist (1980) for the semi-log model specification capturing the true percentage change of a dummy variable given by $= 100[\exp([\alpha]) - 1]$.

Partial Regression analysis

The semi-partial regression is used to express the specific portion of variance explained by a given independent variable within the regression analysis (Abdi, 2002; 2007). Indeed, this approach is primarily employed for non-orthogonal linear regression to assess the specific effect of each independent variable on the dependent variable (Larsen & McCleary, 1972), where the partial regression coefficient or partial slope coefficient value is dependent upon the other independent variables included in the regression equation. Within the traditional OLS setting the multiple regression is extended to find a set of partial regression coefficients *bk* such that the dependent variable could be approximated as well as possible by a linear combination of the independent variables. Therefore, a predicted value, denoted Y, of the dependent variable is obtained as:

$$b\ Y = b0 + b1X1 + b2X2 + \ldots bkXk + \cdots + bKXK. \tag{3}$$

The value of the partial coefficients are found using ordinary least squares (OLS). It is often convenient to express the multiple linear regression equation using matrix notation. In this framework, the predicted values of the dependent variable are collected in a vector denoted b y and are obtained using:

$$b\ y = Xb \text{ with } b = (XTX)-1XTy. \tag{4}$$

Geographically Weighted Regression Model

Geographically Weighted Regression has been used extensively within research studies examining spatial (temporal) variations in market pricing as a consequence of both neighbourhood and locational factors. The approach allows coefficients to vary continuously over the study area, and a set of coefficients can be estimated at any location – typically on a grid so that a coefficient surface can be visualised and interrogated for relationship heterogeneity. GWR makes a point-wise calibration around each regression point where nearer observations have more influence in estimating the local set of coefficients than observations farther away (Fotheringham et al. 1998). In essence, GWR measures the inherent relationships around each regression point i, where each set of regression coefficients is estimated by weighted least squares. As outlined by Fotheringham *et al*. (2002):

$$y_i = \beta_0(x_i, y_i) + \sum \beta_k (x_i, y_i) x_{ik} + \varepsilon_i \tag{5}$$

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

Within this study, the weighting scheme Wi is calculated with a kernel function based on the proximities between regression point i and the N data points nearby. A number of kernel functions can be used for the weighting scheme, a plethora of kernel densities which can be implemented can have varying impact upon ratio study performance[16]. In GWR, an nXn spatial weights matrix is constructed to indicate the weight applied to each observation, assigned relative to the subject based on geographic distance:

$$w_{ij} = exp[-d_{ij}/b^2] \tag{6}$$

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

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

Spatial Lag Model

We estimate a hedonic function in log-linear form and test for the presence of spatial autocorrelation and estimating specifications that incorporate spatial dependence, which captures both the direct and indirect effects of a neighbourhood's housing attributes that are inherently spatial in nature. In this study, we follow the work of Anselin (1988) and Kim (2003) and distinguish between spatial dependence in the form of a spatially lagged dependent variable. Formally, the SLM is expressed as:

$$y = \rho W y + X\beta + u \tag{7}$$

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

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

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

$$y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} u \tag{8}$$

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

$$(I - \rho W)^{-1} = I + \rho W + \rho^2 W^2 + \ldots \tag{9}$$

The reduced form thus expresses the house price as a function not only of the own characteristics (X), but also of the characteristics of neighbouring properties (WX, W^2X), albeit subject to a distance decay operator (the combined effect of powering the spatial autoregressive parameter and the spatial weights matrix). β is often described in the literature as “own-region partial derivatives” that captures the “direct effect” arising from X, whereas ρ is treated as the cumulative cross-partial derivative measuring the “indirect effect” stemming from y through W (LeSage, 2014). In addition, omitted variables, both property-specific as well as related to neighbouring properties are encompassed in the error term[17]. In essence, this reflects a scale mismatch between the property location and the spatial scale of the attributes that enter into the determination of the equilibrium price[ii]. In our analysis, we test the connectivity matrices as (an inverse) power function of geographical distances to account for the best spatial weighting approach to be adopted. In doing so we examine three commonly used specifications in the literature for $W_{i,j}$, namely (i) inverse distance (i.e. $W_{i,j} = 1/d_{i,j}$), (ii) inverse distance squared (i.e. $W_{i,j} = 1/d_{i,j}^2$) and (iii) inverse exponential distance (i.e. $W_{i,j} = 1/e^{d_{i,j}}$) with $d_{i,j}$ denoting the Euclidean distance between property i and property j. The spatial weights approach $W_{i,j} = 1/e^{d_{i,j}}$ produced the most optimal ‘goodness of fit’ with regards to the Adjusted R^2 and AIC.

The model was run incorporating this weighting structure which uses the average of spatially lagged price information of other properties, thereby accounting for spatial dependencies in the residuals[18][iii]. Incorporating EPCs into the framework gives Equation 10 which examines the interaction between *EPC* and the spatial autocorrelation of property prices.

$$\begin{aligned} P_i &= W_{exp}P_j + EPC + W_{exp}P_j * EPC + constant + Area + Appartment + Terraced + \text{detached} \\ &+ \text{Pre1919} + \text{Interwar} + \text{Postwar} + \text{Early}_{\text{moder}} + + \text{Gas}_{\text{heat}} + NoGarage + \epsilon \end{aligned} \tag{10}$$

where: $W_{exp}(\text{In})P_j = \sum_1^n W_{i,j}P_j$; denotes a weighted average of spatially lagged price information of other properties with $W_{i,j} = 1/e^{d_{i,j}}$, $d_{i,j}$ denotes the Euclidean distance between property i and property j. and $(W_{exp}P_j * EPC)$ is the interaction term, which tests whether the variation of spatial autocorrelation in house prices depends on the EPC score[19].

[17] For a full discussion see Anselin, L. and Lozano-Gracia, N. (2008) Errors in variables and spatial effects in hedonic house price models of ambient air quality, *Empirical Economics*, *34*(1), 5-34.

[18] Hence the SL residuals should not be distinguishable from random noise.

[19] The above equations are estimated using OLS. It must be highlighted that Maximum Likelihood methods are commonly utilised for spatial modelling in the hedonic literature given the bi-directional relationship between property prices – the sale price of one house determines and is determined by that of another house in the vicinity. In our analysis, current prices are assumed to be affected only by past prices, not the other way around. Therefore, the spatial lag terms in our models are not endogenous. In light of this, the *OLS* methods produce asymptotically efficient and consistent estimators under the *Gauss-Markov* assumptions.

Results and Findings

The basic semi-log OLS models (Models 1 and 2) encompassing spatial location (dummies) for both EPC score and EPC bands is presented in Table 6. The overall model explanations show relative performance (adjusted R^2) of 67.2% and 67.1%, with all coefficients generally conforming to expectation in terms of sign and significance[20]. The coefficient estimates show that floor area is the most influential (t = 34.316, p<.001; 33.664, p<.001), as expected, signifying that a one metre squared increase in property floor area adds 0.7% in value. With regards to property age, the findings show older properties add more value - arguably reflective that older properties tend to be larger. Both the terrace property and the apartments coefficients are negative displaying percentage effects of -33% and -8.8% for both models respectively. Gas heating type is statistically significant showing that a property with gas heating commands a premium of 14.1% and 14.8%. Pertinently, the EPC coefficient is statistically significant (t= 2.049, p<.001) illustrating that a unitary increase in EPC score increases value by 0.1%. When considering the EPC bands, bands G, F and E conform to expectation revealing negative pricing effects however are not statistically significant at any conventional level. Alternatively, Bands C and B both show positive pricing effects (4.6% and 9.2%), with only band B being statistically significant (Table 6).

<<<Table 6 OLS base model coefficients>>>

Altering the model specification by including interactive variables to examine the effects of EPC scores for each property type and age (Models 3 and 4) as observed in Table 7 presents some noteworthy results. The type by EPC interaction shows terrace properties to be negative, with detached properties showing a positive significant relationship (t= 3.971, p<.01), and apartments negative and statistically significant at the 1% level[21]. The results thereby infer a premium effect for detached properties with a discount effect attributable to both the terrace and apartment sectors. In terms of the age interaction (Model 4), both pre1919 and inter-war period properties exhibit statistically significant positive effects with EPCs with early-modern showing a negative discount which is statistically insignificant. Interestingly, the age classifications suggest that the older (pre1919) properties exhibit a higher pricing effect which may be explained by these properties being larger and comprising traditional features. These findings may be reflective of the complex and confounding relationships – namely the comparison of similar property types in different market areas. For example, an energy efficient house located in a more desirable area may illustrate a high(er) premium or discount because of the location effect, not the energy performance level.

<<<Table 7 OLS interactive models for property age and type>>>

Partial regression modelling

In light of these potential confounding and spatial differences, an interesting dimension of examining EPCs relates to the compartmentalisation of the modelling process. As highlighted by Fuerst *et al.* (2016), it is important to acknowledge that untangling and isolating the effect of a single variable on the price of a house presents methodological challenges. In this regard, further permutations of the OLS model architecture are undertaken to analyse the magnitude and significance of EPCs within various partial regression model forms to test the partial effects of the EPC parameter. The OLS model was therefore constructed to define predictor sets to examine overlap in explanation under identified predictor set categories (Table 8). The property characteristics (floor area; type; age; heating) are separated from the EPC explanatory parameter to derive a series of additive models which partition the explanation into unique and shared components. A base model including only property size with EPCs

[20] Parsimonious model presented. Spatial and temporal dummies are not presented due to space limitations as there are 51 Wards (administrative delineated boundaries) used for controlling for location.
[21] Against the semi-detached holdout properties.

indicates that EPCs are not a statistically significant coefficient (p>.05) with 58.0% of the variation in house prices is explained solely by floor area, only 0.01% solely by EPCs and only 0.03% of shared explained variance. Integrating property type into the predictor set increased the model explanation to 66.2% with the physical characteristics accounting for 65.9% with the EPC coefficient remaining insignificant (p>.05). Notably, only when the gas heating type coefficient is included within the modelling specification, in conjunction with the other physical characteristics (Model 5), does the EPC coefficient become statistically significant at the 5% level (t =2.037, p<.05). Further model alterations interacting EPCs with property type and age within the partial regression predictor set were undertaken (Models 6-8). Interestingly, the results show (without the inclusion of the gas heat coefficient) terrace and detached properties to be statistically significant with apartments being statistically insignificant. However, the inclusion of the gas coefficient results in the apartment x EPC coefficient turning negative and statistically significant at the 1% level (Models 6-7). This finding suggests that apartments with the market availability or amenity of gas (provision) have a negative EPC effect and those apartments without gas heat reveal no significant effect.

To examine the spatial dimension, the partial regression OLS is augmented by integrating a second order trend surface (Models 9-10) which is incorporated as the spatial predictor using X, Y's based on a polynomial expansion method (X, Y, X^2, Y^2, $X*Y$). This is undertaken in order to account for, and reduce, any potential spatial error and residual autocorrelation in the partial regression framework (Table 9). Undertaking this second-order trend surface increases the model R^2 explanation, albeit marginally and confirms that EPCs appear to comprise a positive effect in the detached sector and negative effects relative to the terrace and apartment sectors respectively.

<<<Table X Partial Regression Spatial Expansion Models>>>

Geographically Weighted Regression

More accurately accounting for absolute location within spatially based modelling frameworks is arguably excluded from any existing research measuring the effect of EPCs. In line with other studies, the OLS conditional mean estimates undertaken in the previous sections highlighted some important findings; however, they do not allow the estimates to fluctuate across the housing market meaning heteroscedasticity, or spatial heterogeneity may also represent differences in the urban environment. In line with the original OLS specifications we test the varying nature of EPCs as evidenced in Table 9[22]. The results reveal that there is manifest spatial heterogeneity and variation for property types namely that terrace properties display a constant negative pricing effect, the detached sector only reveals a negative pricing effect at the minimum statistic with apartments showing negative pricing effects up to the 3rd quartile with the maximum coefficient statistic only comprising a positive effect. These negative and positive pricing effects are also evident for the age categories, again highlighting the sizeable spatially varying nature of the coefficient values. Overall, the spatial nature of the coefficients reveals that there are distinctive topographical market structures and indeed segmentation attributable to the property characteristics which command differences in market pricing. These structural characteristics show distinctive and clustered spatial concentrations; nonetheless, in a general spatial sense, this presents a complex mosaic of prices patterns and market composition.

<<<<Insert Table 9 Original GWR model results>>>

In terms of the effects of EPCs, the degree of the varying impact on value ranges from a negative 0.314%, with a maximum effect illustrating a positive 0.418% influence (Figure 2). This is a noteworthy finding as the market mean coefficient for the OLS models suggests that there appears a uniform 0.1% positive effect within the market – further highlighting that studies which have only analysed the

[22] Due to space limitations only the essential coefficients are presented. Full results can be obtained upon request.

conditional mean estimate using OLS may be misleading in terms of the truer nature of the wider 'market value' of the 'EPC effect'. In terms of the spatial varying nature, it is noteworthy that only the minimum coefficient value for EPCs is negative, with the lower quartile showing a zero value. The effects therefore seemingly appear to be not priced in at the lower end of the market, but look to have an increased effect at the upper quartile and maximum value range. As observed in Figure 2, the EPC coefficient appears to exhibit differential pricing effects within two distinct areas in the city centre, towards the south west of the city, and the eastern corridor area where energy efficiency appears to command no premium, with the area towards the north-east indicating a premium effect. Conversely, there also appears a pocket in the south-eastern region of the market area where energy efficiency appears to have a discount effect and is negatively priced in the market with the remainder displaying no real evidence of a premium effect.

<<<Figure 2 GWR Model coefficients>>>

Further refining the GWR model to test the spatial interaction between the structural characteristics for the type of property and EPCs also shows some disparate effects of EPCs (Table 10). Terrace properties show a negative pricing effect across the coefficient range estimates from -0.96% to 0.37% which only becomes positive at the maximum value. In contrast, detached properties display a negligible impact at the minimum value (0.15%) however reveal a small positive effect across the remaining quartiles and showing a maximum value of 0.46%. Apartments depict a similar pricing effect as the detached sector showing EPC pricing effects ranging from -0.46% to 0.46% displaying a negative effect until the median statistic value. With regards to spatial interaction between property age and EPC score, Pre1919 properties exhibit a pricing effect ranging from -0.29% to 0.47% with the negative effect only observed at the minimum value, and positive from the lower quartile value. Early modern properties reveal a lesser range of -0.27% to 0.29%, with Inter-war period properties revealing an effect of -0.12% to 0.32%.

<<<Insert Table 10 EPC interactive effects for type, age and gas>>>

In terms of spatial representation, terrace properties show a relatively consistent pattern with more peripheral locales indicative of both a reduced and increased premium and discount effects. The detached sector whilst displaying evidence of the spatially varying nature of the performance effects of EPCs, also exhibits more geographic pockets of spatial aggregation in central areas which reveal positive pricing effects and a concentrated area which reflects a negative effect towards the north-east of Belfast lough. Apartments also reveal a more consistent spatial depiction in terms of pricing effect, nonetheless there is evidence of both positive and negative pricing hotspots in particular locations to the south-east of the city centre and in peripheral areas of the market.

Examination of the property Age and EPC interactions reveal some noteworthy topographical market structures. The pre1919 age category shows two distinctive market geographies where there appears to be a negative market pricing effect (Figure 3), with a positive premium evident to the south-west. Interestingly, as observed in Table 10, the pre1919*EPC estimates show the negative association to be at the lower end of the price distribution signalling that these two respective districts are perhaps more socio-economically deprived. The early-modern era also displays distinctive bands radiating across the market, with negative pricing associated to the east and towards the south-east. A positive association is more evident in the north and towards the north-west of the Belfast market, highlighting that EPCs for early modern properties comprise a pricing effect ranging from -0.279% to 0.30% (Table 10). For Inter-war period housing, this same pricing effect is noticeable, however the effect is positive from the lower quartile value inferring that these properties tend to have a positive EPC effect across the price strata. With regards to their spatial representation, there also appears localised concentrations of both positive and negative effects with distinct enclaves in the north, south and towards the east showing premiums, with more negative enclaves observed close to the inner city urban core (Figure 3). Finally, when interacting the gas heating and EPC variables, the spatial representation of the interaction term indicates that the city centre and just north of the city centre region of the metropole reveal limited premium effects. This is a pattern generally observed across the entirety of the metropolitan area with the largest premium effect noticeable in a small pocket to the west of the Belfast housing market.

<<<Insert Figure 3 GWR coefficients for Interactive Type, Age and Gas EPC coefficients>>>

Spatial Lag Model Results

Table 11 presents the three-stage model development and estimation using the SLM to examine whether there is spatial autocorrelation between property prices and EPCs. When including the spatial lag term (Model 14) to examine the presence and degree of spatial autocorrelation in property prices the coefficient value equates to 0.0297. This indicates that property prices are correlated over space - signalling that high (*low*) priced housing geographically clusters with other houses with high (*low*) prices, although it must be caveated that the coefficient is not statistically significant at any conventional level. Similarly, the EPC coefficient remains positive but beyond the 5% level of statistical significance. Further incorporating the interaction term into the model structure to capture the (market) dynamics between the spatial lag term and EPC shows the coefficient on the spatial lag term to remain positive (ρ =0.18) and become statistically significant at the 5% level. It is further noteworthy that the EPC coefficient on the interaction term is negative (θ=*-0.0030*) and statistically significant at the 5% level. This implies that property types with low EPCs tend to cluster as lower EPCs give rise to higher spatial autocorrelation - unlike high EPCs which tend to be spatially randomised. These findings are in line with our previous results examining the underpinning spatial structure between the pricing and EPC relationships, and indeed the spatial expansion outcomes, thereby signalling significant spatial randomness in property prices with respect to EPCs. This therefore infers that an increase (decrease) in the value of EPCs tends to weaken (enhance) the strength of spatial autocorrelation in property prices. Put another way, EPCs show a negative spatial autocorrelation effect with a small spatial clustering of house prices (as expected) but the relationship between EPCs and house prices is spatially randomised (correlated) for high- (low-) EPC dwellings.

<<<Table 12 Spatial Lag Models>>>

Discussion

The various modelling procedures and tests have displayed some important insights as to the market pricing of energy performance and particularly the spatial distribution of EPCs. The traditional OLS model exhibits the EPC coefficient to be positive and statistically significant, inferring that superior energy efficiency is considered and priced as a positive housing attribute, albeit marginally. Traditional terrace housing reveals a sizable discount effect with a discount for apartments also evident suggesting that energy efficiency may be already capitalised into the pricing behaviour of market buyers for this property type. A key finding from the OLS modelling shows the terrace property type to be of foremost concern, with the interaction model indicating that terrace properties of pre1919 age category should be targeted by policy to improve energy performance. The model testing scenarios, through the interaction terms revealed some idiosyncrasies, namely that older properties comprise positive effects, with early-modern properties statistically insignificant, suggesting a capitalisation effect or reflective of value enhancing period features.

The partial regression analysis also highlighted this finding, indicating limited shared variance between property size, physical characteristics and EPCs, although it was further established that the value significant effect of EPCs were sensitive to the inclusion of the presence of gas heating which should be included in future modelling scenarios to control for omitted variable bias and mis-attribution as an energy price effect. Indeed, the inclusion of this coefficient impacted unilaterally upon the apartment sector inferring that there is a market perception or behaviour regarding energy performance in this property type and its respective pricing. Accounting for the spatial dynamics in the partial regression framework (polynomial expansion) notably illustrated that the spatial dimension was not a value significant feature of EPCs and vice versa - a finding which was further contextualised within the wider spatial modelling approaches. The GWR analysis exhibited spatial variation and heterogeneity pertaining to the effects of EPCs on value which illustrated that differential pricing effects exist across the market with the level of the effects dissimilar for property type and age. Significantly, this showed both positive and negative effects across the market setting and market differentiation in the perceived value of, and preference for energy performance. This appears evident in terms of market uptake and structure as particular locales appear to show price premiums for superior EPC scores, whereas in other areas there appears no evidence of a premium existing. This finding is critical for policy discourse and the future targeting of policy to alleviate poor energy efficiency in specific market areas in order to achieve energy carbon reduction and realise neutrality in the existing housing stock. Whilst the GWR model variations indicated spatial segmentation, the SLM further tested for, and revealed, that the housing market structure across the BMA demonstrates aspects of spatial aggregation and clustering in terms of pricing - however signalled that EPCs do not wholly reflect this position given that building energy performance was observed to depress spatial autocorrelation of house prices.

The limited evidence of spatial aggregation or spatial randomness is perhaps reflective of behaviour, and more specifically adoption and uptake, or the lack thereof. Indeed, it may be the case that policies tailored towards grant funding for improving energy performance are not spatially targeted in an aggregated sense, and more pertinently, the adoption of enhancing energy efficiency is income dependent and aligned to the availability of sequential market features such as access to the gas network.

Conclusion

Energy efficiency remains a fundamental policy concern for all governments committed to addressing climate change. At the secular level, the targeted reduction of carbon emissions and neutrality within the sphere of the built environment is perceived as one of the most strategic in order to foster change and meet the demands of going 'green' and reduction of carbon emissions. Within the housing realm, the introduction of mandatory energy performance labelling for residential properties reflects a growing emphasis on tackling carbon emissions and abating climatic change challenges. Indeed, whilst the core remit of energy certification is to augment wide scale adoption by influencing buyer perception and behaviour through increased savings, transparency and an observed capitalisation premium, research, to date, has not tended to investigate the variation of EPCs in the wider market (spatial) setting.

This paper contributes to the real estate valuation literature, valuation profession and policy, in that it provides a market transaction price-based empirical assessment of how property values can be spatially affected by the presence of energy performance. Pertinently, it has added to this literature base by conducting analysis into the effects of EPCs combining various differing spatial modelling methodologies at the intra-urban level to assess to level of spatial aggregation between EPCs to establish a more accurate representation of how, or if, the market values EPCs differently. In order to do so, we account for possible endogeneity, heterogeneity, spatial variation and autocorrelation, the distinction between direct effects and the role of a spatial multiplier through the interaction term to establish an evidence base of the EPC premium effect across the market geography.

In line with extant studies, OLS estimation provides a strong basis for revealing EPCs to comprise a marginal pricing effect. Nonetheless, the GWR findings yielded more localised spatially varying coefficients, displaying substantial spatial variability and self-similarity over short distances, suggesting that this approach accounts for intra-urban spatial variability of EPCs exhibiting different degrees of the effect. To ascertain the degree of spatial dependency between the varying nature of the house price-EPC relationship over space, the SLM findings showed no real presence of an intra-urban agglomeration effect further reinforcing the spatial differentiation between pricing, EPCs and market structure thus pointing towards instances of both capitalisation and concessionary effects. Of significance, and importance for other work, is that the lack of spatial aggregation and dependence between house prices and EPCs infers that the capitalisation effect is not always present and that high house prices do not always connote superior energy efficiency. Equally, low house prices do not always portray poor energy efficiency again questioning the capitalisation effect evidenced in studies which reveal mean conditional model estimates. This 'cosmopolitan' EPC-pricing effect presents some demanding challenges for effective policy implementation for the existing housing stock.

In attempting to isolate the effect of EPCs, this research using a partial regression framework showed the importance – for the Belfast market – of EPCs and heating type, namely gas heating which when included together increased the significance of the EPC coefficient. This composite effect reveals the importance of the mis-attribution effect which can result in mis-interpretation of the actual impact of EPCs in being a value determining commodity. Moreover, the findings indicate that merely controlling for location at market delineated geography - through mean conditional estimates - does not accurately account for the spatial variation of EPCs relative to property prices. To state that EPCs have a positive effect on value is imprecise when more accurately controlling for space. The findings show that there is inconsistent and fluctuating pricing effects of EPCs (lack of EPC clustering and lack of interconnection between high house prices and EPCs) illustrating that government should evaluate the effectiveness of its environmental policies and that intervention through policy initiatives needs refined and tailored in order to attain a high level of/ greater city-wide energy efficiency. On the other hand, our SLM analysis conclusively indicates that low-EPC dwellings, of which the majority are low-end housing in Northern Ireland, tend to agglomerate in certain geographical localities. This seemingly represents a substantial opportunity for the relevant planning policy makers to more strategically direct resources toward addressing building energy efficiency issues such as public education on the propagation and potentials of building retrofits and advocation of greener building measures in a more spatially-oriented fashion with geographically broad-based policy initiatives, particularly in communities of deprivation and hardship.

In addition, it must be noted that, this research does comprise a number of data limitations in terms of missing determinants of energy efficient features and property condition. The inclusion of these, whilst not impacting upon the spatial variation of the EPCs, can increase model predictability and more latent understanding of the pricing effects. In this regard, further research should attempt to garner more granular insights in terms of matching these property energy features/characteristics with pricing in spatial econometric approaches. Moreover, future research should examine the intricacies and idiosyncrasies of EPCs in their spatial context and also the performance of EPCs and house prices in terms of their respective strata within a quantile regression setting to isolate and establish if higher or lower priced properties value EPCs more. In addition, more longitudinal studies are also required to capture the effects of change over time and to examine seasonal variability in market uptake for energy efficient features – particularly cost.

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Endnotes

[i] For this analysis, the Moran's *I* reveals the initial distance class to exhibit a small positive and statistically significant *p*-value (0.006, $p<.05$), indicating a spatial clustering of high (low) values. This turns negative (and significant, $p<.05$) across the geographic distance units highlighting spatial dispersion which is often reflective of competitive process - a feature with a high value repels other features with high values; similarly, a feature with a low value repels other features with low values. The spatial representation remains statistically insignificant and

shows no autocorrelation illustrating that the spatial distribution of house prices is the result of random spatial processes or complete spatial randomness (CSR). For EPCs, there is also a nominal level of autocorrelation evident at varying spatial distances. The Moran's *I* is initially positive and statistically significant (p<.001) signalling slight aspects of spatial clustering. However, this turns negative and significant also reflective of spatial randomness and competitive market processes in operation. In addition, the Local Indicator of Spatial Autocorrelation (L.I.S.A) analysis (see Anselin, 1995) for house prices reveal the spatial distribution of the local autocorrelation structure to appear relatively consistent across the market geography with the exception of a few small clusters centrally located.

In turn, the EPCs show a more pronounced and localised autocorrelation (R= .456, *rho*=.223), which remains present at the short-distance geographic units. The bimodal structure of the spatial EPC data is reflective of two distinct underpinning relationships symbolising distinct local trends for EPCs – arguably a result of the complex and dynamic heterogeneity of property type, age, size and geography or a result of new build estates pepper-potted throughout the market geography. Confirmation of this spatial structure is also tested employing Ripley's *K* function measure for spatial aggregation (homogeneity) - whether features, or the values associated with features, exhibit statistically significant clustering or dispersion over the range of truncated distance classes using nearest neighbour methods[i]. Under CSR, deviations from the expected value at each distance, t, are used to construct tests of CSR with critical values. The results reveal marginal deviation of the expected values against the observed at the initial spatial units suggesting an aspect of small clustering (p>.05), with more random dispersion at the larger distances (p<.05) against the theoretical (expected). For EPCs, the results show a random dispersion and inhibition. These initial investigations of the spatial structure demonstrate that there is instances of autocorrelation evident across the spatial structure of the market and therefore some confounding effects of space (LeSage and Pace 2009).

[ii] This study develops a series of models in order to test the effects of the EPC parameter. A SLM is specified without spatial lags to form the base model. We incorporate and test for the significance of a spatially lagged dependent variable. The spatial autocorrelation structure of house prices incorporates a spatial autoregressive term, $\sum_{j=1}^{n} W_{i,j}P_{j,t-k}$, into the model. Where $P_{j,t-k}$ denotes the logarithm of sale price of property j at time *t-k* where k is the number of months prior to the transaction of property i. From a price discovery viewpoint, given the illiquidity of the Northern Irish property market relative to other regions of the U.K., we set k equal to three months. In other words, property traders rely on sale prices of properties transacted within three months prior to the current transaction when determining $P_{i,t}$. $W_{i,j}$ is an $n \times n$ spatial weight matrix governing the fashion in which sale prices of i and j are correlated over space.

[iii]
$$P_{i,t} = c + \rho\sum_{j=1}^{n} W_{i,j}P_{j,t-k} + Area + GasHeat + NoGarage + Apartment + Terraced + Detached + Pre1919 + Interwar + Postwar + Earlymodern + EPC + \epsilon$$

Given that $\sum_{j=1}^{n} W_{i,j} = 1$, the spatial lag term $\sum_{j=1}^{n} W_{i,j}P_{j,t-k}$ represents a weighted average of spatiotemporal lagged price information. ρ is a parameter to be estimated, which measures the degree of "spatial lag" of property prices. If property prices are spatially autocorrelated, then ρ should be non-zero and statistically significant. Thus, $W_{exp}(\mathrm{In})\mathrm{P}_j = \sum_1^n \mathrm{W}_{i,j}\mathrm{P}_j$ [iii] and $\mathrm{W}_{i,j} = 1/e^{d_{i,j}}$, $d_{i,j}$ denotes the Euclidean distance between property i and property j.

Tables and Figures

<<< Table 1 Variable Descriptions>>>

Variable	Description	Type
Sale Price	Transaction price	C
In(Price)	Log of transaction price	C
Floor area	Size of Floor area in m^2	C
Property Type	Type of property (transformed to binary e.g. 1 if Terr; 0 otherwise)	B
Property Age	Age of property (transformed to binary e.g. 1 if Pre1919; 0 otherwise)	B
Heating Type	Type of heating (transformed to binary e.g. 1 if gas; 0 otherwise)	B
Garage	Garage present (transformed to binary e.g. 1 if Garage; 0 otherwise)	B
EPC score	Energy efficiency score	C
Sale period	Date of sale period (transformed to binary e.g. 1 if Q3 2013; 0 otherwise)	B
Sale Date[1]	Date of transacted sale	C

NB. C = continuous; B = binary. [1]For geostatistical (GWR; SLM) models only.

<<< Table 2 Sample representativeness >>>

Variable	Obs.	%
Terrace	408	27.604
Semi-detached	528	35.724
Detached	408	27.604
Apartments	134	9.066
Elec Heat	29	1.962
Gas Heat	523	35.385
Oil Heat	915	61.908
Solid Heat	11	0.744
NB_Post1980	442	29.905
Pre1919	130	8.795
Early Modern	380	25.710
Post War	265	17.929
Inter War	261	17.659
No Garage	569	38.498
Garage	909	61.502

<<<Table 3 Descriptive Statistics>>>

	Sale Price	(In)Price	Floor Area	EPC
Minimum:	24,500	10.106	31	16
Maximum:	900,000	13.71	447	85
Range:	875,500	3.604	416	69
1st Quartile:	90,000	11.408	85	44
Median:	130,000	11.775	104	55
3rd Quartile:	197,500	12.193	141	65
Mean:	164,182	11.818	122.74	54.129
S.E. of Mean:	3015.85	0.016	1.543	0.391
Std. Deviation:	115,944	0.605	59.33	15.042
Skewness:	2.311	0.226	1.964	-0.247

Kurtosis:	-21.991	-0.044	-14.146	1.725

<<<Table 4 Descriptive statistics by property type and age>>>

		Minimum	Maximum	Mean	Std. Dev.	n
Apt	Sold Price	29,500	240,000	110,060.07	40520.94	
	In Price	4.47	5.38	5.01	0.17	134
	Current EPC	19	84	56.03	15.19	
Detach	Sold Price	54,000	900,000	258,961.27	141154.54	
	In Price	4.73	5.95	5.36	0.22	408
	Current EPC	19	83	54.54	15.02	
Semi-Detach	Sold Price	44,000	785,000	152,737.20	87120.98	
	In Price	4.64	5.89	5.14	0.19	528
	Current EPC	18	83	53.26	15.03	
Terr	Sold Price	24,500	675,000	101987.25	66918.32	
	In Price	4.39	5.83	4.94	0.23	408
	Current EPC	16	85	54.22	15.01	
Inter War	Sold Price	25,000	900,000	162,282.97	132,895.19	
	In Price	4.4	5.95	5.09	0.31	261
	Current EPC	19	83	55.15	15.07	
Post War	Sold Price	31,000	535,000	144,982.45	80,421.41	
	In Price	4.49	5.73	5.1	0.23	265
	Current EPC	16	83	53.85	15.42	
Early Modern	Sold Price	24,500	800,000	157,032.48	110,621.80	
	In Price	4.39	5.9	5.12	0.25	380
	Current EPC	18	85	53.64	15.11	
Pre1919	Sold Price	30,000	785,000	201,084.62	185,275.09	
	In Price	4.48	5.89	5.15	0.36	130
	Current EPC	18	83	52.74	15.41	
NB-Post1980	Sold Price	44,000	765,000	172,105.75	97,205.79	
	In Price	4.64	5.88	5.18	0.21	442
	Current EPC	19	84	54.52	14.64	

<<<Table 5 OLS Model Selection procedure sorted by Akaike Information Criterion (AICc)>>>

Model Num.	Variables (#)	No. Vars	R^2	Cond. Num.	AICc	Delta AICc	L(gi|x)	AICc wi
339	1, 2, 3, 4, 6, 8, 9, 11, 12, 13	10	0.674	2.214	-1390.84	0.413	0.813	0.023
342	1, 2, 3, 4, 6, 8, 9, 13	8	0.673	2.198	-1390.75	0.509	0.775	0.022
373	1, 2, 3, 4, 6, 9, 13	7	0.673	2.152	-1390.65	0.605	0.739	0.021
353	1, 2, 3, 4, 6, 8, 11, 12, 13	9	0.673	2.214	-1390.15	1.111	0.574	0.016
347	1, 2, 3, 4, 6, 8, 10, 11, 13	9	0.673	2.212	-1389.81	1.446	0.485	0.014
291	1, 2, 3, 4, 6, 7, 8, 11, 13	9	0.673	2.183	-1389.77	1.488	0.475	0.013
370	1, 2, 3, 4, 6, 9, 11, 13	8	0.673	2.194	-1389.77	1.49	0.475	0.013
338	1, 2, 3, 4, 6, 8, 9, 11, 12, 13	10	0.674	2.248	-1389.76	1.497	0.473	0.013
341	1, 2, 3, 4, 6, 8, 9, 12, 13	9	0.673	2.234	-1389.7	1.559	0.459	0.013

372	1, 2, 3, 4, 6, 9, 12, 13	8	0.673	2.192	-1389.67	1.584	0.453	0.013
99	1, 2, 3, 4, 5, 6, 8, 11, 13	9	0.673	2.204	-1389.59	1.672	0.434	0.012
357	1, 2, 3, 4, 6, 8, 13	7	0.672	2.169	-1389.49	1.765	0.414	0.012
276	1, 2, 3, 4, 6, 7, 8, 9, 11, 13	10	0.674	2.219	-1389.32	1.935	0.38	0.011

NB. Parameter estimates averaged across 8,191 OLS models using Akaike Weights (AICc wi)
#1:FloorArea;#2:Terr;#3:Detach;#4:Apt;#5:Elec;#6:Gas;#7:Solid;#8:Pre1919;#9:Earlymodern;#10:PostWar;#11:InterWar;#12:No Garage;#13:EPC

<<<Table 6 OLS semi-logarithmic price model>>>

	Model 1			*Model 2*		
Variable	*β*	*t*	% Effect	*β*	*t*	%Effect
Constant	10.995	253.845***		11.17	279.803***	
Floor Area	0.007	34.316***	0.70	0.007	33.664***	0.70
TERR	-0.408	-16.6***	-33.5	-0.404	-16.274***	-33.24
DETACH	0.102	3.97***	10.74	0.103	3.973***	10.85
APT	-0.092	-2.453***	-8.79	-0.087	-2.176***	-8.30
Pre1919	0.06	1.732*	6.18	0.064	1.758*	6.61
Early Modern	-0.029	-1.279	-2.86	-0.025	-0.978	-2.57
Inter War	0.037	1.442	3.77	0.041	1.439	4.19
No Garage	-0.019	-0.971	-1.88	-0.028	-1.134	-2.82
Gas Heat	0.132	6.358***	14.11	0.138	6.048***	14.80
EPC score	0.001	2.049**	0.1			
EPC Band G				-0.119	-0.945	-11.22
EPC Band F				-0.035	-0.956	-3.44
EPC Band E				-0.003	-0.114	-0.030
EPC Band C				0.045	1.145	4.60
EPC Band B				0.088	3.008***	9.20
N	1,478			1,478		
R^2	0.674			0.674		
Adj. *R^2*	0.672			0.671		
F-stat	303.074***			188.999***		
AICc	1075.641			1086.035		

***denotes significance at the 1% level; **5% level; * 10% level. %effect = $^e(\beta)$-1.
Parsimonious model presented. Spatial and temporal dummies are available upon request.
For the Banded model, Band D is the hold-out category.

<<<Table 7 Semi-log OLS interactive models for property age and type>>>

Model 3	Model 4

Variable	β	VIF	t	% Effect	β	VIF	t	% Effect
Constant	11.058		362.115***		11.049		368.901***	
Floor Area	0.007	1.573	34.486***	0.70	0.007	1.566	34.61***	0.70
Terr					-0.405	1.463	-16.586***	-33.50
Detach					0.103	1.624	3.990***	10.85
Apt					-0.081	1.401	-2.173**	-7.78
Terr x EPC	-0.406	1.483	-16.512***	-33.37				
Detach x EPC	0.102	1.624	3.971***	10.74				
Apt x EPC	-0.086	1.413	-2.308**	-8.24				
Pre1919	0.058	1.194	1.661	5.97				
Early Modern	-0.029	1.201	-1.285	-2.86				
Inter War	0.039	1.194	1.503	3.98				
Pre1919 x EPC					0.001	1.168	1.986**	0.10
Early Modern x EPC					-0.0007	1.159	-0.67	-0.07
Inter War x EPC					0.0008	1.155	2.073**	0.08
Gas Heat	0.131	1.216	6.277***	14.00	0.131	1.221	6.276***	14.00
No Garage	-0.018	1.058	-0.95	-1.78	-0.018	1.059	-0.947	-1.78
N	1,478				1,478			
R^2	0.673				0.673			
Adj. R^2	0.671				0.671			
F-stat	335.552***				335.812***			
AICc	1077.832				1077.059			

***denotes significance at the 1% level; **5% level.
Parsimonious model presented. Spatial and temporal dummies are available upon request.

<<<Table 8 Partial Regression Models>>>

Variable	Model 5		Model 6		Model 7		Model 8		Model 9		Model 10	
	β	t	β	T	β	t	β	t	β	t	β	t
Constant	10.984	236.915	11.062	424.019***	11.039	419.784***	10.875	419.864***	11.47	1.781*	11.262	38.189***
Predictor Set {A}												
Floor Area	0.007	33.83***	0.007	35.798***	0.007	35.511***	0.008	45.47***	0.007	34.19***	0.007	34.573***
Terr	-0.407	-16.47***							-0.408	-16.597***		
Detach	0.103	3.987***							0.101	3.916***		
Apt	-0.091	-2.337**							-0.094	-2.513***		
Pre1919	0.063	1.731*							0.134	6.409***		
Early Modern	-0.027	-1.027							0.059	1.699		
Inter War	0.04	1.385							-0.029	-1.288		
Gas Heat	0.129	6.282***							0.036	1.984**		
Predictor Set {B}												
EPC	0.001	2.037**							0.001	2.155*		
Terr x EPC			-0.359	-15.452***	-0.384	-16.472***					-0.405	-16.466***
Detach x EPC			0.091	3.509***	0.103	3.983***					0.103	3.983***
Apt x EPC			<.001	0.081	-0.086	-2.348***					-0.088	-2.362***
Pre1919 x EPC							-0.124	-3.337***			0.058	1.664
Early Modern x EPC							-0.008	-0.334			-0.029	-1.274
Inter War x EPC							<.001	-0.946			0.038	1.485
Gas Heat					0.132	6.428***	0.079	3.698***			0.128	6.249***
*X*Y*									0.0013	0.008	0.001	-0.87
*Y*Y*									0.0034	1.481	0.003	0.862
*X*X*									0.0018	0.03	0.002	0.832
N:	1,478		1,478		1,478		1,478		1,478		1478	
R^2:	0.674		0.662		0.671		0.586		0.675		0.673	
Adj. R^2	0.672		0.661		0.67		0.585		0.672		0.671	
F-stat:	302.7***		720***		600.03***		521.1***		202.2***		274.4***	
AICc	1076.561		1117.8		1078.9		1416.09		1081.3		1081.1	
Total {A}	0.673		0.583		0.583		0.583		0.674		0.673	

Total {B}	0.003	0.37	0.389	0.008	0.004	0.002
Total {A+B}	0.674	0.662	0.671	0.586	0.674	0.673
[A.B]{A} only	0.67	0.292	0.282	0.582	0.671	0.671
[A:B] Shared Variance	0.002	0.291	0.301	<0.001	0.003	0.001
[B.A]{B} only	<0.001	0.079	0.088	0.007	0.001	0.001
[1-(A+B)] Unexplain.	0.326	0.338	0.329	0.41	0.325	0.327

***denotes significance at the 1% level; ** 5% level; * 10% level.

<<<Table 9 GWR Model coefficients>>>

	Model 11				
Variable	Minimum	Lwr. Quartile	Median	Upr. Quartile	Maximum
Constant	10.6523	10.8884	10.9599	11.0526	11.2886
Floor Area	0.00498	0.00588	0.00656	0.00694	0.00902
Terr	-0.59563	-0.44609	-0.41486	-0.3731	-0.28155
Detach	-0.11537	0.04578	0.10972	0.14814	0.29126
Apt	-0.29614	-0.19128	-0.07577	-0.02955	0.10419
Pre1919	-0.18167	0.00603	0.08354	0.11088	0.25293
Inter War	-0.07604	-0.01486	0.00994	0.0570	0.23241
Early Modern	-0.14111	-0.08204	-0.0412	0.003	0.1531
Gas Heat	-0.00848	0.08066	0.13001	0.19696	0.28224
EPC Score	-0.00314	0.00001	0.00224	0.00294	0.00412
N	1,478				
R^2	0.720				
Adj R^2	0.715				
F-sat	27.432***				
AICc	1128.349				

NB: Spatial function: Bi-Squared; Adaptive Kernel: 15% neighbours; Optimization using the Golden Section Search and the Akaike Information Criterion (AICc). R^2 is a pseudo R^2 statistic. ***denotes significance at the 1% level.

<<<Table 10 GWR Type, Age and Gas EPC Interaction Results>>>

	Model 12				
Variable	Minimum	Lwr. Quartile	Median	Upr. Quartile	Maximum
Terr x EPC	-0.00962	-0.00698	-0.00586	-0.00542	-0.00365
Detach x EPC	-0.00154	0.00151	0.00227	0.0031	0.00456
Apt x EPC	-0.00455	-0.00203	-0.0002	0.00038	0.00457
Pre1919 x EPC	-0.0029	0.00029	0.00162	0.00256	0.0047
Early Modern x EPC	-0.00279	-0.00111	-0.00039	0.0004	0.00295
Inter War x EPC	-0.00118	0.00021	0.00062	0.00124	0.00316
Gas Heat x EPC	-0.00021	0.00143	0.00209	0.0033	0.00591

NB: Spatial function: Bi-Squared; Adaptive Kernel: 15% neighbours; Optimization using the Golden Section Search and the Akaike Information Criterion (AICc). R^2 is a pseudo R^2 statistic. ***denotes significance at the 1% level. Only EPC statistics presented, full models are available upon request.

<<<Table 11 Spatial Lag Models>>>

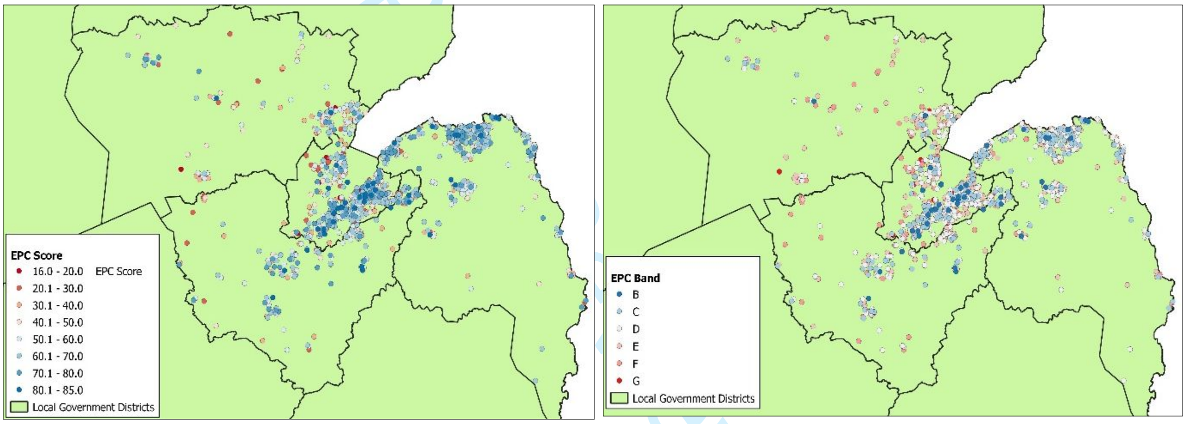
	Model 13 (Base No lag)		*Model 14 (Base + Lag)*[1]		*Model 15 (Base+Lag + EPC)*[1]	
Variable	β	t	β	t	β	t
Constant	10.9829	233.2693***	10.64857	38.19565	8.806233	9.207948***
Floor Area	0.006611	33.88551***	0.006795	28.6727***	0.006796	28.72439***
Terr	-0.398965	-15.9981***	-0.36092	-11.56670***	-0.363045	-11.64686***
Detach	0.099087	3.837041***	0.100533	3.242625***	0.102709	3.316137***
Apt	-0.079251	-1.934257*	-0.056519	-1.173586	-0.057789	-1.201785
Pre1919	0.054449	1.484746	0.030529	0.710688	0.035264	0.821004
Early Modern	-0.020627	-0.790323	0.007467	0.226569	0.007792	0.236813
Inter War	0.04319	1.496247	0.030309	0.850356	0.024715	0.6924

Gas Heat	0.128549	6.05882***	0.108793	4.202728	0.10717	4.14469***
No Garage	-0.017509	-0.907136	0.000841	0.035559	0.001888	0.079952
EPC	0.001248	2.05993**	0.001204	1.671947*	0.036022	2.081373**
W*$\boldsymbol{P_{i,j}}$			0.027939	1.195744	0.184266	2.273019**
W*$\boldsymbol{P_{i,j}}$*EPC					-0.002952	-2.013548**
R^2	0.614722		0.673818		0.675209	
Adj. R^2	0.612213		0.669689		0.67075	
F-stat	268.903***		163.1962***		151.4399***	
AICc	0.747277		0.715859		0.713668	
Log likelihood	-503.7225		-330.9704		-328.9177	
N	961		961		961	

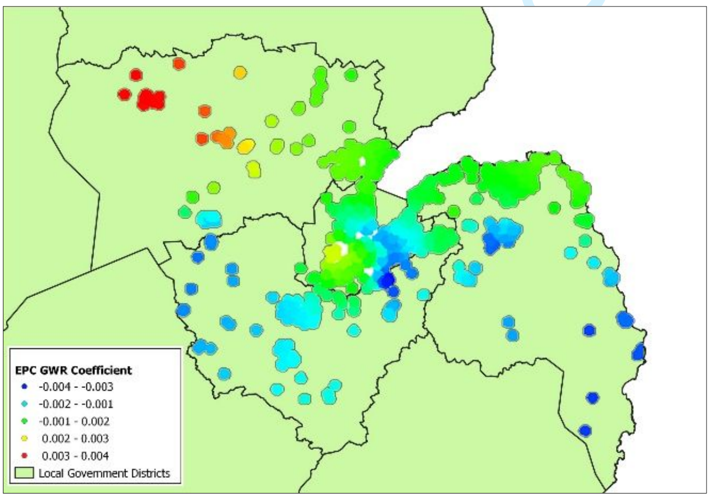
[1]inverse exponential distance models. ***denotes significance at the 1% level; **5% level; *10% level.

Figures

Figure 1 Property EPC scores and bands



<<<Figure 2 GWR EPC score coefficients>>>



<<<Figure 3 Property type, Age and Gas EPC coefficients>>>