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Abstract

Purpose: The role of energy efficiency and particularly Energy Performance Certificates (EPCs) has emerged as a topical and important aspect of real estate markets. Various studies have been carried out investigating the perceived capitalisation effects of energy efficiency on property prices. There remains however divergence of opinion whether the capitalisation effect is truly in existence with extant research showing differing magnitudes of effects, if any. To date, no study (that we are aware of) has investigated the nature of the transition between EPC bands and price effects. The purpose of this study is to add to the research of the energy efficiency of housing to examine the nature of the likelihood of property characteristics being associated with higher EPC scores and value.

Design: This research undertakes a suite of methodological tests to investigate the more latent relationships between EPC bands and pricing behaviour using 3,797 achieved sales prices within the Belfast housing market. Binary logit regression models are specified in conjunction with a Polytomous Universal Model in order to examine the likelihood of EPC bands falling within a particular property type and the likelihood of any pricing effects.

Findings: The findings show the differing property types to comprise very distinct and complex relationships in terms of price and EPC banding. The binary logit model estimations for both terrace properties and apartments reveal an increased likelihood to obtain higher EPC scores, with the semi-detached sector displaying a 'mixed effect' with detached property revealing decreased probability of having superior energy performance and decreased likelihood of having poorer energy performance. The ordinal model estimations indicate that sales price comprises no relationship with energy performance, inferring that there is no increased probability of an increase in sales price with higher EPC rating.

Originality/Value: This research offers new insights and focus on achieving a better understanding of the nexus between energy performance and property characteristics using alternative modelling approaches. This provides more exploratory insights into the complex relationships and offers awareness for policy discourse in terms of targeting properties which will tend to be poorer in energy efficiency.

Keywords: Energy efficiency, Energy performance, Property value, Ordinal regression, Binary logit regression, EPCs.

Introduction

The growing concern pertaining to climate change has seen an increasing policy focus on improving the environmental performance of the housing stock (Högberg and Fuerst *et al.,* 2013). Following the introduction of the Kyoto Protocol in 1997, and more recently the Paris agreement (2016), the reduction of energy consumption attributable to buildings remains a key government policy objective. In Europe, the Energy Performance in Buildings Directive has moved mandatory energy performance disclosure to the forefront of the energy and climate change policy agenda. Whilst seemingly proactive, as Fawcett and Boardman (2009) contend, despite the sustained focus on enhancing construction technology to reduce the carbon emissions for new housing stock, this does not impact upon the existing stock which represents approximately 90% of total market stock and where energy policy tackling efficiency is truly needed. Energy performance labelling is intended to inform potential buyers or occupiers about the intrinsic energy performance of a building and aid occupiers or future potential buyers with information that they can consider, as part of their decision-making process on investment and energy consumption (Fuerst *et al*., 2011). As highlighted by Davis et al. (2015) the introduction of such market-based policy instruments is intended to provide accurate and standardised information to enhance the transparency of energy consumption and incentivise behaviour change in the real estate sector (Brounen and Kok, 2010; Ayers *et al*., 2009; Costa *et al.,* 2010).

Nevertheless, although Energy Performance Certificates (EPCs) appear straightforward conceptually, assessing their impact is challenging and remains an issue for debate. Brounen and Kok (2011) highlight that the process of EPC implementation has been slow with evidence limited. Despite such contentions, there is a burgeoning body of research which has examined the impact of EPCs (Brounen and Kok, 2011, Hyland et al, 2013 and Fuerst et al, 2015; Davis et al., 2015; Olaussen et al., 2017). The general findings tend to show evidence of positive relationships between EPCs and property pricing, although in some cases the results are inconclusive with regards to whether higher EPCs command a price premium. Given that energy performance and its association with pricing is likely to be non-linear (Fuerst et al., 2014), there is also a question as to whether any impact is homogenous across residential sectors and price range, an aspect which remains largely unexplored and arguably limits the ability to accurately assess and understand the significance of energy performance in the house pricing mechanism.

This study is distinct from the majority of extant literature which tends to measure EPC effects using hedonic methodologies, typically with a log-linear specification. As an alternative approach, we examine likelihood effects, using logit and ordinal regression based methodologies. This approach is of significance as it tests the likelihood and transmission effects of EPCs within the price distribution accounting for specific property characteristics. It therefore evaluates the inter-relationships between property characteristics, EPCs and value. It is a novel approach in this subject area to characterise the probability of the likelihood of superior or reduced energy performance occurring. In this regard, segmented typology models are produced to establish the likelihood of energy performance being characteristic of the property type and value, with a further ordinal (EPC banded) model produced to establish the odds ratio effect. Indeed, this compliments wider research examining energy in buildings which scrutinises the heterogeneity of building stock and typology models for measuring the impact of energy efficiency measures. This approach should help policy development and discourse into the dynamics of energy performance and offer insights pertaining to energy performance targeting – which property type and profile and how government should evaluate the effectiveness of its environmental policies for the existing housing stock.

Literature

There is an established and rich literature base investigating the nature of energy and housing with seminal studies stemming back to the 1980s which examined the marginal pricing effects of energy efficiency in housing (Halvorsen and Pollakowski, 1981; Gilmer, 1989; Dinan and Miranowski,1989). Since then, the literature base has developed significantly, primarily due to the enhanced focus upon carbon emissions and abatement. In line with this is the increasing awareness, and requirements, placed upon government(s) to proactively incentivise the drive towards carbon neutrality. Indeed, wider legal directives and initiatives emerging since the beginning of the century has revived the focus of sustainability and energy efficiency within the real estate sector. Accordingly, numerous international studies have been conducted examining the role and pricing of energy efficiency within residential property. One of these primary studies undertaken by Berry et al. (2008), for the Australian Bureau of Statistics, revealed evidence of price premiums with the seminal European research undertaken by Brounen and Kok (2011) also revealing a premium of 3.6% against non-labelled properties. Similarly, Kahn and Kok (2014) and Cerin et al. (2014), examined the differences between property types and against labelled versus non-labelled dwellings. In their study Kahn and Kok (2014) employed a sample of matched dwellings and established a premium effect of 2% for green labelled dwelling comparable to non-labelled properties. Interestingly, Cerin et al. (2014), found evidence of price premiums within particular housing age segments built before 1960 indicating that particular housing segments require policy targeting.

For England, Fuerst et al. (2015) utilised a large sample of 325,950 observations to measure to EPC effects, revealing 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 discounts were estimated at −0.7% and −0.9% respectively. In line with Cerin et al. their results revealed differential effects relative to property type with increased premiums noted for terrace properties and apartments in comparison to semi-detached and detached properties. by Fuerst et al. (2016) undertook a further study for the Welsh housing market drawing on a sample of approximately 192,000 transactions. They found positive price premiums for properties with 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%) significant discounts were noticeable. These findings are also in keeping with the study conducted by Hyland et al. (2013), who in an Irish context also analysed the effect of energy efficiency ratings on property prices. The results displayed positive price premiums evident for A classifications (9%), B (5%) and C (1.7%), relative to D-rated dwellings.

Studies have found weaker or limited evidence of premium or capitalisation effects of EPCs. Looking specifically at the apartment sector, Fregonara et al. (2014) evaluated the impact of EPCs on list prices for the Turin housing market. 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. Davis *et al.* (2015), for the Belfast housing market, Northern Ireland, investigated the relationship between EPCs and property prices. The authors revealed a nominal positive relationship (0.4%) between better energy performance and higher selling prices, although noted that energy efficiency remains complex and difficult to accurately quantify given the idiosyncratic nature of property as an asset class. Indeed, they advocated that further research in this area, including widening the pool of knowledge on the actual performance of the housing stock and into the marginal energy efficiency and pricing effect of products and practices is therefore warranted. This is analogous to the findings of Olaussen, Oust and Solstad (2017) who explored EPCs and primarily their effect pre and post EPC introduction into the Norwegian housing market. The authors indicate that any price premium associated with energy labels is largely inconclusive and partly contradictory. In a follow up paper, Davis *et al.* (2017) further examined the role of energy performance in the wider housing stock from a property taxation perspective. Using a Computer Assisted Mass Appraisal (CAMA) methodology 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 – revealing that significant differences in terms of 'good' energy performance relate to spatial aggregation and can be measured in the population of housing stock.

The literature has evolved with studies examining energy efficiency in a time series or spatial orientated framework. Aroul and Rodriguez (2017) examining the temporal variations in green premiums, make a compelling argument not to generalize findings for one market across markets that have different climates or attitudes regarding green amenities, recommending that policymakers should develop more tailored programmes that help lower income individuals gain access to the growing benefits of green amenities. Similarly, concentrating on the apartment sector, however in a more spatial approach, Taltavull, Anghel and Ciora, (2017) investigate the impact of energy performance on transaction prices in Bucharest. Concentrating on retrofitted apartments they specified a STAR GLS model in order to evaluate the diffusion effect of house prices spatially by sub-market. Their findings suggest a green premium in two market areas between 2.2% and 6.5% with further Spatial diffusion effects revealed to contribute positively to house prices, nonetheless highlighting that the unobserved spatial component reduces this effect. In a further spatial context, McCord et al. (2019) investigated the significance of EPCs at the inter and intra-neighbourhood level. Their findings yielding more localised spatially varying coefficients, displayed substantial spatial variability of EPCs. The incorporation of a Spatial Lag Model within their methodology showed no real presence of an intra-urban agglomeration effect illustrating that the spatial differentiation between pricing, EPCs and market structure revealed instances of both capitalisation and concessionary effects. Of significance, and importance, the study found a lack of spatial aggregation and dependence between house prices and EPCs inferring that the 'cosmopolitan' EPC-pricing effect presents some demanding challenges for effective policy implementation for the existing housing stock. In a more behavioural study, Amecke (2012) evaluated the adoption and impact of energy performance certificates based on a survey of 1,239 private purchasers in Germany. They found limited effectiveness of EPCs for incorporating energy efficiency in their purchasing decisions. Likewise, Warren-Myers, Judge, and Paladino (2018) reveal that 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.

In a not to dissimilar line of inquiry, a strand of research has developed examining the heterogeneity of building stock and typology models and more specifically enhancing modelling techniques to investigate the impact of energy efficiency measures (EEM). Numerous research studies (Galante and Torri, 2012; McKenna et al., 2013; Aksoezen et al., 2015; Mastrucci, Baume, and Stazi, 2015; Kragh, and Wittchen, 2014 and Swan and Ugursal, 2009) have investigated and developed enhanced methodologies for building-stock descriptions using building-specific data and measured energy use to augment an age-type building-stock classification for estimating energy cost, consumption and performance. As outlined by Österbring *et al.* (2016) traditionally, the description of the building-stock generally comprises an age-type classification to specify building characteristics for groups of buildings, however they point out that these descriptions lack the appropriate level of detail to differentiate the potential for EEM within age groups (Aksoezen et al., 2015). Indeed Österbring et al (2016) integrated building characteristics from energy performance certificates in Gothenburg, for measuring energy use revealed that at the individual building level further refinements in terms of methodological enhancements are necessary. Accordingly, the classification and errors in measurement somewhat relate to pricing studies which have not tested the nature and examined the heterogeneity of the typical housing stock for energy efficiency 'signals' and may therefore result in measurement error.

The existing literature clearly highlights that energy efficiency comprises differential pricing effects, *if any*, with premium or capitalisation effects evident in some studies and more conservative findings either revealing negligible price premium effects or indeed no premium effect evident. Indeed, the mixed findings serve to highlight a number of issues in terms of controlling for endogeneity and the inclusionary characteristics within the modelling frameworks which may present confounding effects or mis-specification or indeed mis-attribution to energy performance. This is further identified in the building-stock-model-based analysis literature of energy performance which illustrates that building (property) characteristics and the heterogeneity of such remains challenging for energy assessment and measurement. Appositely, for pricing studies, a key issue relates to studies which only use one property type in comparison to those hedonic based studies which attempt to analyse the performance across the entirety of the sales sample. As Lyons (2013) posits, the different findings are arguably conditional on the country, region or physical attributes, which the research of Cerin et al. (2014) and Baumont (2017) further indicate the results are determined by housing segmentation as the energy performance relationship differs according to the type of housing and thus particular housing segments need policy targeting and support. This paper is clearly positioned in this debate and seeks to add the literature base by identifying the extent to which energy labelling impacts upon the pricing effect using both binary and ordinal approaches to investigate the transmission effects within sectoral models and across EPC bands.

Data and Methodology

Data

This study presents an exploratory investigation using the Belfast residential housing market, UK - the largest urban conurbation with the highest level of transaction-based prices and property stock across the jurisdiction of Northern Ireland. The study uses 3,964 observations which were subject to outlier removal and data entry checks leaving 3,797 observations for analysis purposes. The data is sourced from the University of Ulster House Price Index (UUHPI) for the period Q3, 2017 to Q3, 2018, providing a representative cross-section of the Belfast housing market region. The UUHPI is an established property market index originating from 1984 which provides achieved transaction prices obtained from a variety of robust and verified sources obtained on a quarterly basis. The UUHPI sample captures 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. Where applicable, the variables were transformed into binary state for hedonic purposes. In addition, 'new build' properties were removed from the sample. This step was undertaken as it is believed that the new build 'premium' tends to skew and distort the pricing effects of EPCs. Table 1 outlines the variables utilised within the investigation and the associated transformations.

The data comprises 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 are missing, we have included the principal physical characteristics and information , which impact upon pricing and EPC scores. This is in line with a paper undertaken by Davis et al (2016)[1] which demonstrated a statistically significant relationship between a

[1] https://doi.org/10.1108/JERER-06-2016-0023

basket of attributes similar to the information applied in this research. Whilst there are potentially challenges in terms of omitted variable bias, as is the case with all regression based models, we have included all the significant features and characteristics available from the data and extended this by blending datasets to capture as many aspects as possible.

<<<Insert Table 1 - Variables within the research study>>>

The descriptive analysis is summarised in Table 2. The sample data shows the average sale price equates to £140,264 with a mean floor area of 121 m^2. The descriptive statistics reveal a mean EPC band D, a maximum score of EPC band B and the minimum being the lowest score G. Notably, an EPC performance rating classification 'Band A' (+92) does not exist within the sample data.

<<<Table 2 Descriptive Statistics>>>

To permit meaningful analysis, the sample size across all property types was scrutinized to confirm representation within the sample dataset (Table 3) relative to the wider market composition[2]. Just over a quarter of the sales sample comprises terraced properties (25.8%), with apartments representing the lowest volume of transactions (461) accounting for 12.1%. Detached properties account for 33.3% of the sample, with semi-detached representing 28.7%.

The highest EPC rating is achieved by apartments with an average score of 86 (Band B), with the average EPC score 54.76 (Band D). With regards to property age, Early-modern housing represents 25% of the sample, with Post 1980 properties accounting for 35.7%. Pre1919 dwellings comprise the least contribution to the data sample accounting for 7.2%, with Inter-war and Post-war period properties accounting for 12.6% and 15.2% respectively.

<<<Table 3 Frequency analysis of EPC bands, Type and Age>>>

Methods

Binary Logistic Regression

Within this research, the dependent variable is transformed into a dichotomous state therefore requiring the generation of models for predictions based on likelihood of a property type and EPC rating (i.e. to predict by measuring variables for the probability of whether a property falls within EPC Band B or C). When attributes are categorical, any assumption of linearity is violated and logistic regression can be used to transform the linear model in logarithmic terms (*logit*) permitting the prediction of categorical outcomes based on the probability of occurrence. Instead of predicting the value of Y from a predictor variable(s) $X_{(n)}$ we examine the dichotomous prediction of probability of Y occurring (P)Y from known values (e = natural logarithms) resulting in probability of Y occurring equating to the case belonging to a particular category culminating in a binary estimation (0; 1).

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[2] Analysis of the stock composition of the Belfast market obtained from the GIS pointer system which records all registered properties reveals the total stock composition comprises 29.25% terrace; 25.34% semi-detached; 35.09% detached and 10.33% apartments.

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i})}} \text{ or } P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i} + b_2 X_{2i} \dots b_n X_{ni})}}$$

A value close to 0 suggests that Y is very unlikely to have occurred, with a value close to 1 implying that Y is very likely to have occurred. This employs a maximum-likelihood estimation procedure which selects the coefficients (β) that make the observed values most likely to have occurred - in essence, the chosen estimates of the βs will be ones that, when values of the predictor variables are placed in it, result in values of Y closet to the observed values. Assessing the model, *the log-likelihood*, is based on summation of the probabilities associated with the predicted, P(Y_i) and actual Y_i, outcomes – this is similar to the residual sum of squares (RSS):

$$\sum_{i=1}^{N} [Y_i In(P(Y_i)) + (1 - Y_i) In\,(1 - P(Y_i))]$$

The model is assessed using the likelihood ratio. This is illustrated in that a negative coefficient value implies that as a predictor value increases, the likelihood of the outcome decreases, with a positive value indicating that as the predictor variable increases, so does the likelihood of the event occurring (Field, 2018). The predictors are assessed within the model by examining the individual 'fit' employing the Wald statistic (z) and odds ratio (Exponential of β). The z statistic[3] indicates whether the b-value for the predictor is significantly different from 0; illustrating its significant contribution to the prediction of the outcome (Y). The odds ratio reflects the exponential of β and is an indicator of the change in odds resulting from a unit change in the predictor, with the odds of an event occurring defined as the probability of an event occurring divided by the probability of the event not occurring:

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i} + b_2 X_{2i} \dots b_n X_{ni})}}$$

Where the Odds:

$$= \frac{P\,(event)}{P\,(no\ event)};\ P(event\ Y) = \frac{1}{1 + e^{-(b_0) + b_1 X_{1i}}}\ ;\ P(event\ Y) = 1 - P(event\ Y)$$

This provides the odds before and after a unit change in the predictor variable, thereby demonstrating the proportionate change in odds (Odds ratio) which can be interpreted as a value exceeding 1 (>1) to show that as a predictor increases, the odds of the outcome occurring increase, with <1 indicating that as a predictor increases, the odds of the outcome occurring decrease.

Polytomous (Multinomial) Universal Model (Proportional odds ratio)

The rationale for undertaking the *Polytomous Universal Model (*PLUM) approach is a logical step for assessing EPC bands, given their ordinal categorical scale of measurement. When the nature of the dependent variable is ordinal this presents significant challenges. When this occurs, the standard approach is to specify a multinomial logit model, however, this ignores any ordering of the values of the dependent variable. Alternatively, the ordinal nature of the dependent variable can be used in an Ordinal Regression procedure, or PLUM, which is an extension of the general linear model to accommodate ordinal categorical data. This

[3] The Wald statistic is the z^2 Chi-Squared distribution.

Cumulative Proportional Odds Model involves specification of link functions for the cumulate probabilities, as well as scaling parameters used to fit heteroscedastic probit and logit models (O'Connel, 2006). As the model is an extension of the logistic regression model for dichotomous data for categorical ordinal data (Zelterman, 1988), this modifies the binary logistic regression model to incorporate the ordinal nature of a dependent variable by defining the probabilities differently. The M**ultinomial Logistic Regression approach** models how multinomial response variable Y depends on a set of k explanatory variables, $X=(X_1, X_2, \ldots X_k)$ based on a GLM where the random component assumes that the distribution of Y is Multinomial(n,$\pi\pi$). The systematic components are explanatory variables (continuous, discrete, or both) and are linear in the parameters, e.g., $\beta_0 + \beta x_i + \ldots + \beta_0 + \beta x_k$.. Again, transformation of the X's themselves are allowed, as in linear regression, with the link function being the generalized Logit. Thus, this linear predictor function constructs a score from a set of weights which are linearly combined with the explanatory variables (features) of a given observation:

$$\text{Score}\,(\mathbf{X_i}\,,\text{k}) = \beta_\text{k} \cdot \text{X}_{\text{i},}\,,$$

where $\mathbf{X}_i$ is the vector of explanatory variables describing observation i, $\boldsymbol{\beta}_k$ is a vector of weights (regression coefficients). corresponding to outcome k, and score($\mathbf{X}_i$, k) is the score associated with assigning observation i to category k. The linear predictor function $f(k,i)$ to predict the probability that observation i has outcome k, of the following form:

$$\text{f(k,i)} = \beta_{0,\text{k}} + \beta_{1,\text{k}}\text{x}_{1,\text{i}} + \beta_{2,\text{k}}\text{x}_{2,\text{i}} + \beta_{\text{M,k}}\text{x}_{\text{M,i}},$$

where $\beta_{\text{M,k}}$is a regression coefficient associated with the mth explanatory variable and the kth outcome.

To arrive at the multinomial logit model, one can imagine, for K possible outcomes, running K-1 independent binary logistic regression models, in which one outcome is chosen as a "pivot" and then the other K-1 outcomes are separately regressed against the pivot outcome. This would proceed as follows, if outcome K (the last outcome) is chosen as the pivot:

$$In\frac{\Pr\,(Y_i = 1)}{\Pr\,(Y_i = K)} = \beta_\text{k} \cdot \text{X}_{\text{i},}\,,$$

$$In\frac{\Pr\,(Y_i = 2)}{\Pr\,(Y_i = K)} = \beta_\text{k} \cdot \text{X}_{\text{i},}\,,$$

……..

$$In\frac{\Pr\,(Y_i = K-1)}{\Pr\,(Y_i = K)} = \beta_{\text{k}-1} \cdot \text{X}_{\text{i},}$$

This introduces separate sets of regression coefficients, one for each possible outcome. If exponentiating both sides, and solving for probabilities, then:

$$\Pr\,(Y_i = 1) = \Pr\,(Y_i = K)e^{\beta_1 \cdot \text{X}_{\text{i},}}$$

$$\Pr\,(Y_i = 2) = \Pr\,(Y_i = K)e^{\beta_2 \cdot \text{X}_{\text{i},}}$$

Or:

$$\Pr\,(Y_i = K-1) = \Pr\,(Y_i = K)e^{\beta_{\text{K}-1} \cdot \text{X}_{\text{i},}}$$

Given that all K probabilities must equal one, then:

$$\Pr(Y_i = K) = 1 - \sum_{k=1}^{K-1} \Pr(Y_i = K) = 1 - \sum_{k=1}^{K-1} \Pr(Y_i = K) e^{\beta_k \cdot X_i} \Rightarrow \Pr(Y_i = K) = \frac{1}{1 + \sum_{k=1}^{K-1} e^{\beta_k \cdot X_i}}$$

We therefore apply this specification to determine other probabilities:

$$\Pr(Y_i = 1) = \frac{e^{\beta_1 \cdot X_i}}{1 + \sum_{k=1}^{K-1} e^{\beta_k \cdot X_i}}$$

$$\Pr(Y_i = 2) = \frac{e^{\beta 2 \cdot X_i}}{1 + \sum_{k=1}^{K-1} e^{\beta_k \cdot X_i}}$$

$$\Pr(Y_i = K-1) = \frac{e^{\beta_{K-1} \cdot X_i}}{1 + \sum_{k=1}^{K-1} e^{\beta_k \cdot X_i}}$$

We estimate a multinomial logistic regression model by specifying the baseline (reference) comparison group (EPC category G). The output therefore comprises a series of equations, for example:

$$In\left(\frac{P(EPC = B}{P(EPC = G}\right) = \beta_{10} + \beta_{11}(Type = Terrace) + \beta_{12}(Type = Apartment) + \beta_{13}(Area)..$$

$$In\left(\frac{P(EPC = C}{P(EPC = G}\right) = \beta_{20} + \beta_{21}(Type = Terrace) + \beta_{22}(Type = Apartment) + \beta_{23}(Area)..$$

Where β's are the regression coefficients. The ratio of the probability of choosing one outcome category over the probability of choosing the baseline category equates to the relative risk or odds. The regression coefficients represent the the change in log relative risk (log odds) per unit change in the predictor. Exponentiating the linear equations yields relative risk ratios. Larger coefficients indicate an association with lager scores. For a continuous variable, a positive coefficient indicates that since the values of the variable increase, the likelihood of higher scores increases. A negative coefficient indicates that lower scores are more similar and close each other. An association with higher scores shows smaller cumulative probabilities for lower scores, since they are less close to occur, Each logit has its own term αj, but the same coefficient β. That means that the effect of the independent variable is the same for different logit function. The ordinal logistic model is based on an assumption that the relationship includes a continuous latent variable and that the ordinal observed result derived from discretization of a underlying continuous variable (Fujikoshi, and von Rosen, 2000).

Spearman's Rho correlation

In this study, as EPC bands are ordinal in scale, the intervals between positions on the scale are monotonic and lacking design to be numerically uniform increments, thus, requiring selection of the appropriate testing procedures. The Spearman's rank-order correlation is the paramount non-parametric method which measures the strength and direction of association between ranked data. In contrast to other correlation procedures, the Spearman's test is employed when variables are ordinal in nature, as it determines the strength and direction of the monotonic relationship between sets of variables, rather than the strength and direction of the linear relationship between them. Therefore, Spearman's correlation measures the strength and direction of a monotonic association between two variables which is 'less restrictive' than that of a linear relationship. Whilst a monotonic relationship is not strictly an assumption of Spearman's correlation, initial testing of the data can determine whether a monotonic component exists in terms of the association to 'best fit' the pattern of the observed data. The Spearman's correlation is specified as follows:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

where d_i = difference in paired ranks and n = number of cases.

The Pearson's test is used to understand the level of association between the EPC scores and house prices. The Pearson's test measures the linear relationship of the linear correlation between two variables X and Y whereby the coefficient is the covariance of the two variables divided by the product of their standard deviations. The formula for is:

$$\rho x,y \frac{cov\,(x,y)}{\delta_x \delta_y}$$

where: *cov* is the covariance, δ_x is the standard deviation of X, with δ_y is the standard deviation of Y.

T-Tests

The Independent Samples T-test compares the means of two independent groups in order to determine whether there is statistical evidence that the associated population means are significantly different. A t-test looks at the *t*-statistic, the *t*-distribution and degrees of freedom to determine the probability of difference between populations. The formula used to calculate the test is a ratio. The portion of the ratio is the difference between the means or averages of the two samples. The lower half of the ratio is a measurement of dispersion, or variability, of the scores. This is known as the standard error of difference.

$$t = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{\frac{S_1^2}{N_1} + \frac{S_2^2}{N_2}}}$$

The t-test offers an analysis of whether there is a statistical difference between EPC bands and prices and allows insights to be drawn.

Findings

As illustrated in the methodology, the nexus between property type, age and EPC bands and price are analysed for their inter-relationships and to establish whether there is a statistically significant difference between each respective band gradation and the accompanying price structure (distribution). Moreover, the findings discussed are based on a series of relationship tests and the development of binary logit regression models and a proportional odds (ordinal) regression approach to establish the likelihood of increased energy performance across type and for each EPC band.

Correlation Analysis

At the overall level, the correlation analysis was run using both the Pearson and Spearman's rho in order to capture the strength and direction of the relationships. Table 4 identifies the correlation coefficients relating to the energy bands and price structure and other property characteristics. The correlation findings reveal a nominal weak positive association between EPC bands and Sold Price (r= .069, p<.001) and a marginal weak negative association with price/m^2 (r= -.089, p<.001). The results suggest that there is a nominal association with the energy banding at the overall level and accounting for the price per size effect this becomes negative. A moderate negative association between Age and EPC bands is evident (r= -.483, p<0) inferring that the age of a property may impact upon its energy efficiency rating. Property size also shows a weak negative relationship (r=-.089, p<.05) indicating that as size increases, EPC rating decreases. This is interesting given the fact that floor area is not a specific efficiency metric in the EPC formulation process – in that larger floor area does not implicitly indicate a worse score.

<<<Table 4 Correlations between all variables>>>

Further examination of the correlation between EPC bands, property type, sale price and the price per square metre clearly highlights some contrasting relationships (Table 5). When disaggregating the data for each respective EPC band per property type, there appears to be some quite distinctive and conflicting relationships which emerge. Figure1 (a-b), reveals this difference, in the magnitude and direction of the correlation coefficients associated with sales price and the price/m^2 ratio.

<<<Table 5 - Correlations between EPCs by property type for Price/m^2 and Price>>>

On a price per square metre basis, all property types except apartments display a negative relationship with EPC band rating B, ranging from -0.121 (p<.05) for terrace housing, -0.178 (p<.10) and -0.257 (p<.01) for detached properties. Apartments, in contrast, show a positive moderate level of association (.385), significant at the 1% level. What is interesting to note is the disparate relationships which emerge when transitioning through the bands. For detached properties, the EPC rating and price per square metre relationship turns positive and increases when moving down the EPC bands, namely, the price per square metre increases as energy performance decreases (Figure 1a). This is also similar for the semi-detached sector where EPC bands B and C show a negative association before turning marginally positive at band C and displaying no real relationship across the remaining bands, which are also statistically insignificant. In terms of terrace properties, the EPC rating and price per square metre shows an (negative) increase in the magnitude when transitioning down towards the lower energy performance rankings, signalling that lower EPC rated properties comprise a higher negative association, all statistically significant, suggesting that as the price per square metre increases energy performance decreases. The apartment sector displays a diminishing level of positive association (and statistical significance) until Band F (0.028,p>.05), illustrating that the level of positive correlation decreases when moving down the EPC ratings, or in other words, as EPC rating increases the price per square metre increases. The results show the inconsistent nature of the EPC price relationships across the market typologies.

<<<Figure 1a Correlation between EPC rating and the Price per square metre>>>

Examination of the correlations on a price basis further reveals some complex and intricate relationships when analysing energy performance (Figure 1b). The detached sector displays a relatively consistent positive association between EPC band and sales price suggesting that across all EPC ratings there is a moderately positive statistically significant relationship. Conversely, for apartments, there is a modest negative association between EPC band B and sales price (-0.605, p<001). This magnitude decreases when moving down the EPC band classifications to band E, which reveals a more negligible negative association (-0.108, p<.001). Both the terrace and semi-detached sectors reveal changes in the magnitude and direction of the correlations when transitioning through the EPC bands, with terrace showing a much more pronounced effect (Figure 4b). The results suggest that in general, there is a complicated association between EPCs on both transacted prices and the price per square metre basis and the magnitude of the effect is not uniform across property segments. Moreover, there are quite contrasting and conflicting relationships which emerge when analysing the nature of the EPC price relationship using the sale price and sale price per meter square ratio.

<<<Figure 1b Correlation between EPC rating and Sale Price>>>

T-tests analysis

T-tests were utilised to scrutinise whether there is a difference in pricing between each of the energy performance bands across the price distribution for each property type (Table 6)[4]. In terms of the findings, the descriptive statistics indicate that generally higher mean prices are observed at the band B EPC classification which decreases at lower bands, though appearing to increase at the lowest band classification (F) for most types – representing some sort of parabolic relationship. An interesting and noticeable observation is that each property type displays some sort of differential effect. There appears a significant difference in the prices of apartments between EPC rating B/C (t=1.814 p=.071), albeit at the 10% level. This however does not hold true for the remaining bands which seemingly suggests that a downward movement through the band range does not show statistically significant changes in apartment prices. For both terrace (5.536, p<.01) and detached (4.987, p<.01) properties, this relationship is also evident, however this is observed at the band C/D categories respectively. For semi-detached properties, there is a statistically significant change in price between E/F categories. Overall, these findings point towards, and perhaps infer, a 'step change' may be evident for each property type in terms of the price and EPC relationship. For apartments this occurs at the upper band level, namely, band B, which shows a difference from the remainder, supporting the hypothesis that a capitalisation effect may be evident between the band classifications and price strata. For terrace and detached properties this capitalisation effect may occur between C/D and semi-detached between E/F.

<<<Insert Table 6 T-test results between EPCs and Price for each property type>>>

Binary logistic regression analysis

The binary models are specified to examine the nature of the explanation by benchmarking each of the distinct property types against the wider market stock (e.g. detached model=1, rest

[4] Null: there is no statically significant difference between EPC band(s) and property price.

of the market=0)[5]. The variables in the simultaneous equation findings equate to regression coefficients which refer to change in log odds or - *logits* as a function of change in predictor variables. This is interpreted as a change in log odds (*or logits*) for every unitary change or increase on predictor variables. A positive value indicates that as scores increase the probability of falling into a target group (for example, detached [=1]) increases. Conversely, a negative coefficient value implies that as scores increase on a predictor variable there is a decreasing likelihood of the observation falling into the property type category. The models are constructed using three sets of covariates, EPC bands, price/m^2 ratio and property age.

The Classification table for the detached model illustrates a 71.5% fit overall[6]. Table 7 illustrates that the values for each EPC band display negative coefficients, signifying that a unitary increase in EPC band comprises a decrease in the likelihood of it being a detached property. When examining the odds ratio (exponential of beta), the results for each EPC band show that the odds of a detached property is lower for a higher EPCs. This indicates that the odds of a detached property are lower by 0.031 for EPC band B, meaning that detached is less likely to be rated an EPC band B. Or alternatively, the odds of a detached property will be lower by 96.9% for an EPC band B relative to the wider market. This effect reduces when moving down the EPC band ranges. For example, there is an odds ratio of 0.57 meaning that the likelihood of an F banded detached property are lower by 43% relative to the wider market. In terms of property age, *Post-1980* is more likely to be a detached property compared to the wider sample of property stock, whereas there is a decrease in likelihood that a detached property is either of *Pre1919* or *Interwar* period. Examining the Price/m^2 coefficient reveals that for every single unitary increase in the Price/m^2, there is an increased likelihood of the property being detached.

The semi-detached model[7] findings show both EPC bands B and C to not be statistically significant, nonetheless it infers that semi-detached properties are 1.26 times, or 26% more likely to have an EPC Band C classification against the wider sample, with an EPC label B circa 38.2% less likely to be in this band classification, relative to the wider sample. For bands D, E and F, there is an increased odds ratio that semi-detached is between 2.113 to 2.353 times greater or 111% to 135% of these properties being in these lower EPC band classifications. The age coefficients illustrate that, with the exception of the Post-war period properties, semi-detached property is less likely to be older, or indeed newer. The price/m^2 coefficient reveals that there is no increased or decreased likelihood that any unitary change in the price per square metre equates to it being semi-detached. In other words, the price/m^2 has no effect on distinguishing whether a property is semi-detached from the remainder of the market sample.

<<<Insert Table 7 Detached and Semi-detached sector odds ratio coefficients>>>

The terrace model[8] (Table 8) illustrates that while moving up the EPC band strata, a terrace property demonstrates a higher percentage effect, thereby inferring a strong positive likelihood of price increase the more energy efficient the dwelling is – relative to the wider property market stock. For EPC band B the odds likelihood indicates that terrace properties are 3.756 times (275%) more likely to have an EPC score than the remainder of the sample housing stock.

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[5] The models are based upon the expectation that if property type is equal to 1, (meaning it is present), thus the wider sample of property stock is equal to zero.

[6] The initial tests exhibit the significant Chi-Square (intercept only) prediction model to fit the data than a null model (non-predictors), revealing a statistically significant improvement in fit with the addition of the characteristic coefficients with the Classification table.

[7] Model classification equates to a 71.3% goodness-of-fit.

[8] Model classification equates to a 81.9% goodness-of-fit.

This odds likelihood increases for EPC band C (4.734) and reduces across the remainder of the EPC bands. The price per square metre shows a negative association, resulting in a log likelihood to be lower in value however obtain a higher EPC score. In addition, the analysis shows that there is an increased log likelihood that the terrace properties are Pre1919 or Interwar period properties relative to the wider market. This presents some interesting results as the *a priori* assumption would tend to suggest that older properties would tend to have poorer EPC labelling.

The apartment sector model[9] clearly demonstrates that an apartment has a 22.13 times greater likelihood to have an EPC score B than the rest of the market (Table 8). This is evident for the EPC rating C and to a significantly smaller degree EPC band D which further reduces across the bands. Both EPC bands E and F show that these EPC categories have a less likely odds ratio (32.9% and 75.6%) of this occurring against the wider housing market stock. In terms of property age, the odds ratio scores clearly reveal apartments to be less likely to be older and more likely to be newer. This was an a priori assumption, as apartments tend to dominate the more modern section in the market.

<<<Insert Table 8 Terrace and Apartment sector odds ratio coefficients>>>

PLUM findings

The PLUM regression approach was further undertaken using the EPC rating (A-G) as the dependent variable, with property characteristics used as factors and size and price variables as covariates within the model architecture. Comparison of the baseline and intercept models illustrates that the statistically significant Chi-Square statistic ($p<.001$) provides a significant improvement over the baseline intercept-only model, thus the explanatory variables enhance the predictive nature of the marginal probabilities for the outcome categories[10]. The Goodness-of-Fit is tested to examine whether the observed data is consistent with the fitted model (Table 9). The Pearson's χ^2 statistic for the model (as well as the deviance) illustrates that the deviance is $p>.05$ thus the model is appropriate for further analysis[11]. In addition, for logistic and ordinal regression models it not possible to compute the same R^2 statistic as in linear regression, so three approximations are computed instead. The pseudo R^2 values (e.g. Nagelkerke = 39.1%; Cox and Snell = 37%) indicates that property age, type and price explains a relatively adequate proportion of the variation between EPC bands.

<<<Insert Table 9 Model fit and Pseudo R^2 statistics>>>

In terms of the parameter estimates, the Wald test and associated *p*-value estimates reveal the individual influence of each explanatory variables in the context of the model. The thresholds are depicted as the shift between levels of outcome variables (i.e. the change between EPC banding/rating). Thus, EPC bands (thresholds) are intercepts, with the coefficient factor and covariate estimates type, age, sale price and floor area slope parameters relating to the EPC

[9] Classification equates to a 89.8% goodness-of-fit.

[10] The log likelihood reflects the measure of error (outcome versus the probability prediction) for the intercept-only and final models, indicating the parameters of the model for which the model fit is calculated. The intercept describes a model that does not control for any predictor variables and simply fits an intercept to predict the outcome variable, with the final describing the model that includes the specified predictor variables whose coefficient have been estimated using an iterative process that maximizes the log likelihood of the outcome. The Chi-Square represents the Likelihood Ratio (LR) Chi-Square test assesses whether at least one of the predictors' regression coefficient is not equal to zero in the model.

[11] The null hypothesis is that the fit is appropriate, therefore if we reject this hypothesis ($p>.05$) then the model predictions are similar and the model is good.

ratings and these represent the log-odds (exponent of odds required for impact of explanatory variables). The type parameters show *terrace* properties to have a positive effect and are more likely to have a higher EPC classification (against the reference category of semi-detached). For the logit link, in terms of magnitude, the cumulative odds ratio (exponential of the estimate) shows that a one unit increase in the coefficient estimate for terrace shows an odds ratio of 1.94 which suggests that the odds of having a higher EPC is 1.94 times higher than semi-detached (Table 10). For detached property, the odds ratio indicates that the odds of a higher rating is 0.50 times lower than the odds of semi-detached. For apartments, the estimates show that the odds of a higher rating are 7.61 times higher than for semi-detached properties.

In terms of comparative ordering, apartments appear to have an increased likelihood to be more energy efficient, followed by terrace properties, semi-detached properties and lastly detached. In light of this, the findings illustrate that the detached sector of the market is where energy policy should be targeted, to enhance energy performance - followed closely by the semi-detached sector. When considering property age characteristics, the estimates reveal axiomatic and obvious patterns. Lower cumulative scores are more likely to be for older properties compared to new build in higher EPC bands. Pre1919 properties comprise the lowest cumulative odds ratio indicative that lower cumulative scores are more likely. Pertinently, this pattern of lower cumulative odds diminishes when transitioning towards newer properties ranging from 99 times less likely to have a higher EPC for Pre1919 properties to 82 times less likely for Post1980 properties. Furthermore, and importantly, examination of both covariates within the model shows *Sale Price* to be negligibly negative, signalling that the change in odds between property pricing and EPCs is somewhat limited revealing no increasing likelihood that higher EPC bands connote increased price, in fact, the negative coefficient suggests otherwise. In essence, increased sales price is more likely to fall into lower EPC categories as opposed to the higher EPC rankings. With regards to the size coefficient, whilst positive, is not a statistically significant predictor.

<<<Insert Table 10 Proportional odds (ordinal) Parameter and Wald Estimates>>>

Discussion

Energy performance remains a challenging and complex area for housing research. Whilst numerous studies have investigated whether higher EPC scores command increased price premiums, there is a more limited strand of the evidence base which examines, especially for policy targeting, which segments of the market are reflective of increased likelihood (probability) of being less or more energy efficient. This research has attempted to offer more latent insights into the inter-relationships between energy performance and the standard characteristics of housing. The results emerging from this research showed that there is a rather complex, almost paradoxical set of relationships in terms of evaluating energy performance. Indeed, initial explorations revealed the contrasting relationship between EPC ratings, sale price and price on a per square metre basis. When considering these associations by each market segment, the direction and magnitude of the associations differed seismically at times (Table 11).

<<<Insert Table 11 Summary of Correlation and T-test results>>>

The logistic and proportional odds (ordinal) logistic regression findings (Table 12) provide some important insights as to the characteristics of each respective property type and their energy performance likelihood. The logistic models were constructed in order to benchmark each property type against the wider market perspective, to garner insights as to whether energy performance is more, or less, likely for each segment. This was further inspected using the ordinal framework which applied each EPC rating to predict the probabilities of the outcomes based on the intercepts. The logistic findings revealed the detached sector overwhelmingly has decreased likelihood of energy efficiency against the sample property stock. In terms of the semi-detached sector, with the exception of EPC band B which shows a decreased likelihood, all other EPC rating show an increase in the likelihood of occurrence relative to the wider sample. This is also similar for the terrace sector which displays an increased likelihood of energy ratings across each respective band, whereas the apartment sector reveals increased likelihood of EPC ratings B, C and D only. Turning to the ordinal model estimations, the findings clearly show the apartment and terrace sectors to exhibit increased likelihoods of superior energy efficiency relative to the semi-detached sector, with the detached showing a decrease in likelihood – thus poorer energy efficiency. Pertinently, the sale price coefficient does not reflect any increased likelihood that increases in sales prices commands higher energy efficiency.

The findings therefore suggest that a complex and dynamic relationship exists between the nature of the property type and its respective energy efficiency and sales price. In terms of policy, the results do suggest that energy abatement policy should target both the detached and semi-detached sectors in order to tackle poor energy efficiency in the Belfast housing market and particularly in the existing stock. The apartment sector is more likely to show increased energy efficiency labelling with the terrace sector presenting more confounding results – arguably reflective of both retrofit activity and the existence of terrace housing stock which has not been upgraded. In respect to policy, the results highlight that different initiatives need to be tailored to different aspects or segments of the property stock. For example – where there is a clear financial incentive to improve energy efficiency, the policy message can clearly emphasise and publicise this. Where there is no clear link, alternative strategies need to be designed which emphasise or leverage other particular behavioural and cultural aspects. This emphasises the need for a balanced 'basket' of policies, which encourage good practice (without relying on public capital resources) whilst also discouraging poor practices. This is only possible with an informed understanding of the nuances of the market behaviour and the knowledge of the housing stock gleaned from research of this type.

<<<Insert Table 12 Logistic and ordinal model finding summaries>>>

Conclusions

Over the past two decades there has been an increasing policy focus on improving the environmental performance of the housing stock. Whilst originally emerging from concerns regarding fuel poverty and associated hardship, this has now taken on more of an environmental focus. Unfortunately we are likely to be dealing with the stock we have been gifted by previous generations for many years to come, requiring positive action on behalf of owners and policy makers, making energy efficiency labelling and other visible metrics of great concern. The core function of mandatory energy efficiency certification in the EU has been to change consumer behaviour by providing reliable information on the energy performance of dwellings to buyers. Indeed, numerous studies have used the hedonic pricing method to establish whether there has been a capitalisation effect of EPCs evidenced by the market for various property types. This study has examined the nature of the relationship in a somewhat different way to traditional hedonic price estimations. Namely, it offers an exploratory foray into the underpinning relationship in terms of the price EPC band movements within property types and the change in structure of this characteristic, to establish whether it impacts on price performance. From this it offers suggestions on what impacts upon the EPC relationship with price.

Based on a probability log-likelihood estimation, the findings show the differing property types to comprise very distinct and complex relationships in terms of price and EPC banding, the *good*, the *bad* and the *indifferent*. The binary logit model estimations for both terrace properties and apartments demonstrated that these types have an increased likelihood to obtain higher EPC scores, although the terrace sector also displayed an increased likelihood of having lower EPC ratings, revealing this sector to have both superior and inferior energy performance. Interestingly, the semi-detached sector revealed less likelihood for higher energy performance rating B but more probability of more 'medium ground' rating (C-E), with detached revealing decreased probability of having superior energy performance and decreased likelihood of having poorer energy performance.

Moreover, the ordinal model estimations indicated that sales price comprises no relationship with energy performance banding, inferring that there is no increased probability of an increase in sales price with higher EPC rating - clearly illustrating the complexity of evaluating whether an energy premium is in effect. This indicates that the complexity of 'property' characteristics that impact on EPC score do not fully account for energy efficiency – in terms of any potential capitalisation effect. Overall, the ordinal regression results illustrate that there is a mixed effect based on the EPC band and property characteristics unique to each segment of the market but does confirm that older properties have an increased odds ratio for a negative effect on energy efficiency - of which the level of the effect diminishes as property age classification becomes newer. In terms of policy discourse and awareness, the findings indicate that for tackling energy efficiency and carbon abatement, uniform, top-down approaches directed at the housing market may not be fruitful or effective, if policy-makers are serious about achieving carbon neutral targets. Indeed, the findings of this research suggest that a more targeted approach per market typology is a necessity – particularly for the detached sector, for realizing superior energy efficiency. Policy makers and the resulting engagement mechanisms need to 'get down in the weeds' and 'get their hands dirty' to properly address the retrofitting issues that affect the housing stock. Given the challenges these findings pose, it is clear that tackling energy efficiency within the existing housing market remains a fundamental challenge. Increased government participation through the procurement of effective tools and more innovative schemes and incentives is crucial, if 2050 targets are to be realised.

References

Aksoezen, M., Daniel, M., Hassler, U., & Kohler, N. (2015). Building age as an indicator for energy consumption. *Energy and Buildings*, *87*, 74-86.

Amecke, H. (2012). The impact of energy performance certificates: A survey of German home owners. Energy Policy, 46, 4-14.

Aroul, R. R., & Rodriguez, M. (2017). The Increasing Value of Green for Residential Real Estate. Journal of Sustainable Real Estate, 9(1), 112-130.

Ayers, S. Raseman, and A. Shih, Evidence from Two Large Field Experiments that Peer Comparison Feedback Can Reduce Residential Energy Usage, NBER Working Paper 15386, 2009.

Bloom, B., Nobe, M., & Nobe, M. (2011). Valuing green home designs: A study of ENERGY STAR homes. *Journal of Sustainable Real Estate*, *3*(1), 109-126.

Brounen, D., & Kok, N. (2011). On the economics of energy labels in the housing market. Journal of Environmental Economics and Management, 62(2), 166-179.

Bruegge, C., Carrión-Flores, C., & Pope, J. C. (2016). Does the housing market value energy efficient homes? Evidence from the energy star program. Regional Science and Urban Economics, 57, 63-76.

Cajias, M Piazolo, D (2013) "Green performs better: energy efficiency and financial return on buildings", Journal of Corporate Real Estate, Vol. 15 Issue: 1, pp.53-72.

Cerin, P., Hassel, L. G., & Semenova, N. (2014). Energy performance and housing prices. Sustainable Development, 22(6), 404-419.

Chegut, A., Eichholtz, P., & Holtermans, R. (2016). Energy efficiency and economic value in affordable housing. *Energy Policy*, *97*, 39-49.

Davis, P. T., McCord, J. A., McCord, M., & Haran, M. (2015). Modelling the effect of energy performance certificate rating on property value in the Belfast housing market. *International Journal of Housing Markets and Analysis*, *8*(3), 292-317.

Davis, P., McCord, M. J., McCluskey, W., Montgomery, E., Haran, M., & McCord, J. (2017). Is energy performance too taxing? A CAMA approach to modelling residential energy in housing in Northern Ireland. *Journal of European Real Estate Research*, *10*(2), 124-148.

de Ayala, A., Galarraga, I., & Spadaro, J. V. (2016). The price of energy efficiency in the Spanish housing market. Energy Policy, 94, 16-24.

Dinan, T., Miranowski, J., 1989. Estimating the implicit price of energy efficiency improvements in the residential housing market: A hedonic approach. J. Urban Econ. 25(1), 52-67.

Fawcett, T., & Boardman, B. (2009). Housing market transformation. *Proceedings of European Council for an Energy Efficient Economy. Summer Study*, 1-6.

Feige, A., Mcallister, P., & Wallbaum, H. (2013). Rental price and sustainability ratings: which sustainability criteria are really paying back?. *Construction Management and Economics*, *31*(4), 322-334.

Fregonara, E., Rolando, D., Semeraro, P., & Vella, M. (2014). The impact of Energy Performance Certificate level on house listing prices. First evidence from Italian real estate. Aestimum, (65), 143-163.

Fuerst F, McAllister P, Nanda A, and Wyatt P (2016a) Energy Performance Ratings and House Prices In Wales: An Empirical Study, Energy Policy.

Fuerst F, Oikarinen E, and Harjunen O (2016b) Green signalling effects in the market for energy-efficient residential buildings, Applied Energy.

Fuerst, F., & Warren-Myers, G. (2018). Does Voluntary Disclosure Create a Green Lemon Problem? Energy-Efficiency Ratings and House Prices. Energy Economics.

Fuerst, F., McAllister, P., Nanda, A., & Wyatt, P. (2015). Does energy efficiency matter to home-buyers? An investigation of EPC ratings and transaction prices in England. *Energy Economics*, *48*, 145-156.

Galante, A., M. Torri, M. (2012) A methodology for the energy performance classification of residential building stock on an urban scale, Energy Build., 48, 211-219.

Högberg, L. (2013). The impact of energy performance on single-family home selling prices in Sweden. Journal of European Real Estate Research, 6(3), 242-261.

Hyland et al. (2013) The value of domestic building energy efficiency—evidence from Ireland. Energy Economics, 40, 943-952.

Kahn, M. E., & Kok, N. (2014). The capitalization of green labels in the California housing market. *Regional Science and Urban Economics*, *47*, 25-34.

Kavgic, M., Mavrogianni, A., Mumovic, D., Summerfield, A., Stevanovic, Z., & Djurovic-Petrovic, M. (2010). A review of bottom-up building stock models for energy consumption in the residential sector. *Building and environment*, *45*(7), 1683-1697.

Kholodilin, K. A., Mense, A., & Michelsen, C. (2017). The market value of energy efficiency in buildings and the mode of tenure. *Urban Studies*, *54*(14), 3218-3238.

Kim, C, W., Phipps, T, T., Anselin, L. (2003) Measuring the benefits of air quality improvement: a spatial hedonic approach, Journal of Environmental Economics and Management, 45, 24-39.

Kok, N., & Jennen, M. (2012). The impact of energy labels and accessibility on office rents. *Energy Policy*, *46*, 489-497.

Kragh, K. and Wittchen, B. (2014) Development of two Danish building typologies for residential buildings, Energy Build., 68, 79-86

Liu, N., Zhao, Y., & Ge, J. (2018). Do renters skimp on energy efficiency during economic recessions? Evidence from Northeast Scotland. Energy, 165, 164-175.

Mastrucci, A., Baume, O., Stazi, F., & Leopold, U. (2014). Estimating energy savings for the residential building stock of an entire city: A GIS-based statistical downscaling approach applied to Rotterdam. *Energy and Buildings*, *75*, 358-367.

Mata, É., Kalagasidis, A. S., & Johnsson, F. (2014). Building-stock aggregation through archetype buildings: France, Germany, Spain and the UK. *Building and Environment*, *81*, 270-282.

McCord, M., Lo, D., Davis, P. T., Hemphill, L., McCord, J., & Haran, M. (2019). A spatial analysis of EPCs in The Belfast Metropolitan Area housing market. *Journal of Property Research*, 1-37.

McKenna, R., Merkel, E., Fehrenbach, D., Mehne, S., & Fichtner, W. (2013). Energy efficiency in the German residential sector: a bottom-up building-stock-model-based analysis in the context of energy-political targets. *Building and Environment*, *62*, 77-88.

Murphy, L. (2014). The influence of the energy performance certificate: The Dutch case. *Energy Policy*, *67*, 664-672.

O'Connel, A.A. (2006) Logistic regression models for ordinal response variables. Thousand Oaks: Sage: London.

Olaussen, J. O., Oust, A., & Solstad, J. T. (2017). Energy performance certificates–Informing the informed or the indifferent?. *Energy policy*, *111*, 246-254.

Österbring, M., Mata, É., Thuvander, L., Mangold, M., Johnsson, F., & Wallbaum, H. (2016). A differentiated description of building-stocks for a georeferenced urban bottom-up building-stock model. *Energy and Buildings*, *120*, 78-84.

Ramos A, Perez-Alonso, A., Silva, S (2015) Valuing Energy Performance Certificates in the Portuguese Residential Sector, Economics for Energy.

Sartori, I., Wachenfeldt, B. J., & Hestnes, A. G. (2009). Energy demand in the Norwegian building stock: Scenarios on potential reduction. *Energy Policy*, *37*(5), 1614-1627.

Stanley, S., Lyons, R. C., & Lyons, S. (2016). The price effect of building energy ratings in the Dublin residential market. Energy Efficiency, 9(4), 875-885.

Swan, L. G., Ugursal, V.I. (2009) Modeling of end-use energy consumption in the residential sector: a review of modeling techniques, Renew. Sustain. Energy Rev., 13 (8), 1819-1835

Taltavull, P., Anghel, I., & Ciora, C. (2017). Impact of energy performance on transaction prices: Evidence from the apartment market in Bucharest. *Journal of European Real Estate Research*, *10*(1), 57-72.

Warren-Myers, G., Judge, M., & Paladino, A. (2018). Sustainability ratings in residential development: a worthwhile endeavour?. International Journal of Building Pathology and Adaptation, 36(4), 353-372.
Zhang, L., Liu, H., & Wu, J. (2017). The price premium for green-labelled housing: Evidence from China. Urban Studies, 54(15), 3524-3541.

Tables and Figures

Tables

<<<Table 1 - Variables within the research study>>>

Variable	Description	Type
Sale Price	Transacted price	C
Size	Floor area in m^2	C
Property Type	Type of property (e.g. 1 if apartment; 0 otherwise)	B
Property Age	Age of property (e.g. 1 if Pre1919; 0 otherwise)	B
EPC rating	Energy efficiency rating in bands (A-G)	O
Price/m2	Ratio of property price by size	C
In(Price)	Log of Price	C
Sale period	Date of sale period (e.g. 1 if Q3 2017; 0 otherwise)	B
Location	Ward property is located (1 if Ward 1; 0 otherwise)	B

C = continuous; B = binary; O = ordinal

<<<Table 2 Descriptive Statistics>>>

	Minimum	Maximum	Mean	Std. Dev
Sale Price	20,000	930,000	140,264	102,239
Type	1	4	2.83	1.02
Floor Area	26	550	121.33	60.59
Price/m^2	83.13	7,655	1,141.9	502.06
EPC Bands	B	G	D	C-E
Age	1	5	3.82	1.34

<<<Table 3 Frequency analysis of EPC bands, Type and Age>>>

EPC band (score range)	Frequency	Percent (%)
EPC a (92+)	0	0.0
EPC b (81-91)	88	2.3
EPC c (69-80)	660	17.4
EPC d (55-68)	1324	34.9
EPC e (39-54)	1111	29.3
EPC f (21-38)	547	14.4
EPC g (1-20)	67	1.8
Apartments	461	12.1
Terrace	980	25.8
Detached	1265	33.3
Semi-detached	1091	28.7
pre1919	272	7.2
Inter-war	479	12.6
Post-war	778	15.2
Early modern	951	25
Post1980	1355	35.7

<<<Table 4 Correlations between all variables>>>

	Type	Age	EPC Band	Floor Area	Sale Price	Pricem2
Type	1					
Age	0.019	1				
EPC band	.321**	-.483**	1			
Floor Area	.664**	.097**	.103**	1		
Sale Price	.582**	.094**	.069**	.063**	1	
Price/m^2	.160**	0.023	-.089**	.063**	.706**	1

**Correlation is significant at the 1% level.

<<<Table 5 - Correlations between EPCs by property type for Price/m^2 and Price>>>

EPC bands	App (m^2)	App	Terr (m^2)	Terr	Det (m^2)	Det	Sdt (m^2)	Sdt
B	0.385***	-0.605***	-0.121**	0.106	-0.257***	0.566***	-0.178*	0.169
C	0.307***	-0.355***	-0.273***	-0.088**	0.102**	0.546***	-0.18**	0.015
D	0.187***	-0.151***	-0.337***	-0.460***	0.163***	0.582***	0.04	-0.063**
E	0.051*	-0.108***	-0.432***	-0.520***	0.364***	0.635***	0.017	-0.13***
F	0.028	-0.73	-0.452***	-0.525***	0.411***	0.541***	-0.014	-0.067
G	0.154	0.027	-0.408***	-0.467***	0.354***	0.479***	-0.054	-0.092

***Correlation is significant at the 1% level, **5% level, *10% level.

<<<Table 6 T-test results between EPCs and Price for each property type>>>

EPC	*N*	*mean*	*std dev*	*f-levenes*	*t*
		Apartments			
B/C	56 / 259	107275 / 95474	42963 / 44391	0.216	1.814*
C/D	259 / 115	95474 / 100879	44391 / 61741	3.254	-0.958
D/E	115 / 25	100879 / 81980	61741 / 46345	0.177	1.443
E/F	25 / 4	81980 / 81250	46345 / 59913	0.234	0.028
F/G	2/4	81250 / 179750	59913 / 141067	5.655	-1.299
		Terrace			
B/C	8 / 159	136625 / 114131	21222 / 59639	5.891	1.061
C/D	159 / 344	114131 / 85495	59639 / 51107	6.401	5.536***
D/E	344 / 305	85495 / 80360	51107 / 60320	0.849	1.174

E/F	305 / 145	80360/ 76055	60320 / 37544	0.744	0.79
F/G	145 / 19	76055 / 89064	37544 / 58349	6.786	-1.32
			Detached		
B/C	14 / 112	223317 /265108	59385 /124053	4.697	-1.24
C/D	112 / 438	265108 /203069	124053/115760	3.104	4.987***
D/E	438 / 427	203069 /206695	115760 /113448	0.008	-0.465
E/F	427 / 238	206695 /213109	113448 / 136475	10.856	-0.649
F/G	238/ 36	213109 /277705	136475 / 233274	19.358	-2.37
			Semi-detached		
B/C	10/130	150485 /124997	51250 / 65787	0.754	1.196
C/D	130 / 427	124997 /119051	65787 / 61651	2.438	0.948
D/E	427 / 354	119051 /114054	61651 / 63571	1.867	1.112
E/F	354 / 160	114054 /128629	63571 / 79041	5.622	-2.226**
F/G	160 / 10	128629 /134800	79041 / 80801	0.397	-0.239

<<<Table 7 Detached and Semi-detached sector odds ratio coefficients>>>

	Detached			Semi-detached		
	β	Wald	Exp(β)	β	Wald	Exp(β)
EPCb	-3.460	65.441***	0.031	-0.482	0.919	0.618
EPCc	-3.020	98.798***	0.049	0.233	0.398	1.262
EPCd	-1.640	33.518***	0.194	0.856	5.745**	2.353
EPCe	-1.043	13.861***	0.352	0.836	5.499**	2.307
EPCf	-0.561	3.850**	0.570	0.748	4.246**	2.113
Pre1919	-1.291	21.375***	0.275	-1.831	36.827***	0.160
Interwar	-1.677	40.511***	0.187	-0.065	0.082	0.937
Post war	-0.613	6.165**	0.542	0.039	0.031	1.040
Early modern	-0.128	0.290	0.880	-0.289	1.791	0.749
Post1980	0.415	3.372*	1.515	-0.395	3.664*	0.674
Price/m^2	0.001	257.651***	1.001	0.000	11.786***	1.000
Constant	-0.590	2.624	0.555	-0.993	5.703**	0.371

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

<<<Insert Table 8 Terrace and Apartment sector odds ratio coefficients>>>

	Terrace/Townhouse			Apartments		
	β	Wald	Exp(β)	β	Wald	Exp(β)
EPCb	1.323	6.071**	3.756	3.097	15.892***	22.134
EPCc	1.555	18.814***	4.734	2.478	11.210***	11.913
EPCd	1.024	8.838***	2.785	0.774	1.094	2.169
EPCe	0.577	2.833*	1.781	-0.398	0.275	0.671
EPCf	0.103	0.085	1.108	-1.411	2.532	0.244
Pre1919	3.330	111.661***	27.926	-1.502	10.649***	0.223

Interwar	2.371	66.379***	10.712	-1.375	16.107***	0.253
Postwar	1.109	14.908***	3.032	-1.184	14.039***	0.306
Early modern	0.749	7.186***	2.115	-0.439	3.125*	0.645
Post1980	-0.026	0.009	0.975	0.001	0.000	1.001
Price/m^2	-0.003	422.382***	0.997	0.001	90.262***	1.001
Constant	-0.067	0.023	0.935	-4.098	27.692***	0.017

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

<<<Table 9 Model fit and Pseudo R^2 statistics>>>

Model	-2 Log Likelihood	Chi-Square (χ^2)	d.f.	R^2
Intercept Only	11096.479			
Final	9339.870	1756.609	10***	
Pearson		21538.508	18265***	
Deviance		9290.495	18265	
Cox and Snell				.370
Nagelkerke				.391
McFadden				.157

Link function: Logit. D.F. represents the degrees of freedom. ***denotes 99% significance.

<<<Table 10 Proportional odds (ordinal) Parameter and Wald Estimates>>>

	Estimate	Wald	95% L. Bound	95% U Bound
EPCb	-17.78	521.238*	-19.306	-16.253
EPCc	-14.637	390.853*	-16.088	-13.186
EPCd	-12.356	287.332*	-13.785	-10.927
EPCe	-10.552	211.606*	-11.974	-9.13
EPCf	-8.03	120.156*	-9.466	-6.594
Sale Price	-0.000268	31.24*	-0.000362	-0.00017
Floor Area	0.002	3.732*	-0.000238	0.003
Apartment	2.08	282.119*	1.838	2.323
Terrace	0.633	53.444*	0.463	0.802
Detached	-0.698	64.6*	-0.868	-0.528
Pre1919	-4.621	474.915*	-5.037	-4.206
Interwar	-4.077	437.149*	-4.459	-3.695
Post-war	-3.56	354.685*	-3.931	-3.19
Early modern	-3.238	319.007*	-3.593	-2.882
Null -2LL	9339.87			
General -2LL	6601.86			
χ^2*	2738.0			

NB. LL equates to Log-Likelihood; ***denotes significance at the 1% level. Null hypothesis states that the location parameters (slope coefficients) are the same across response categories. a. Link function: Logit. b. The log-likelihood value cannot be further increased after maximum number of step-halving. c. χ^2 statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain

<<<Table 11 Summary of Correlation and T-test results>>>

	Correlation (direction, magnitude)	**T-test (sig. diff)**
Sale Price	Marginally positive	
Price/m^2	Marginally negative	
APP (m2)	Positive to Band E	
App	Negative to Band E	B and C
Ter (m2)	Negative and increasing through the remaining Bands	
Ter	Positive for B, increasing negative for remaining Bands	C and D
Det (m2)	Negative B, positive and increasing for remaining Bands	
Det	Positive and equivalent for all remaining Bands	C and D
Sdt (m2)	Negative for B and C, positive for D and E, negative for E and F	
Sdt	Positive for B and C, negative for remaining Bands	E and F

NB. sig. diff equates to the rejection of the null hypothesis: there is no statistical difference in prices

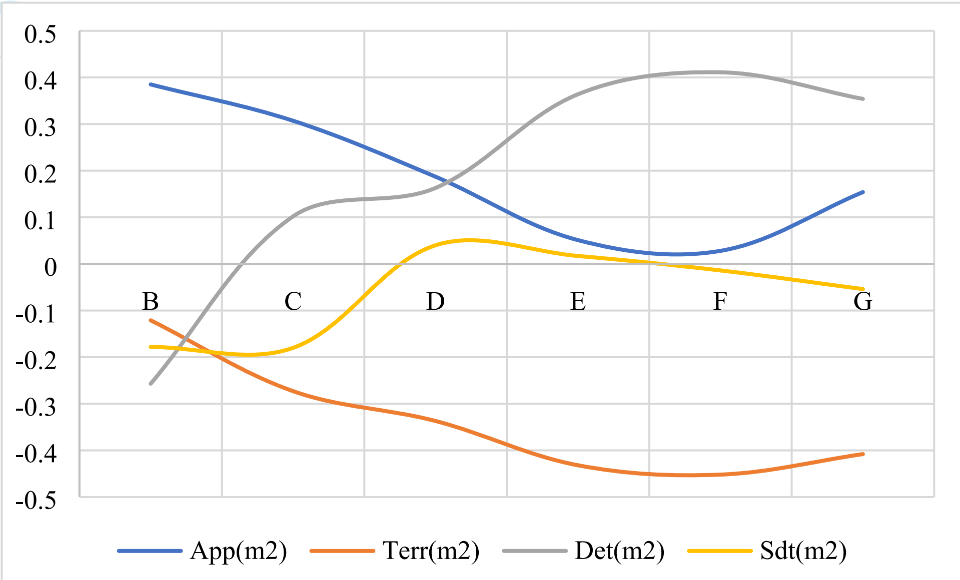
<<<Table 12 Logistic and ordinal model finding summaries>>>

	Logistic model Likelihood				Ordinal model Likelihood
	Det	Sdt	Ter	Apt	
EPCb	↓	↓	↑	↑	
EPCc	↓	↑	↑	↑	
EPCd	↓	↑	↑	↑	
EPCe	↓	↑	↑	↓	
EPCf	↓	↑	↑	↓	
Pre1919	↓	↓	↑	↓	↓
Interwar	↓	↓	↑	↓	↓
Post war	↓	↑	↑	↓	↓
Early modern	↓	↓	↑	↓	↓
Post1980	↑	↓	↓	↑	↑
Price/m^2	↑	↔	↓	↑	
Sale price					↓
Floor area					↑
Apartment					↑
Terrace					↑
Detached					↓

NB. ↔ equals no effect; ↑ increased likelihood; ↓ decreased likelihood

Figures

<<<Figure 1a Correlation between EPC rating and the Price per square metre>>>



<<<Figure 1b Correlation between EPC rating and Sale Price>>>