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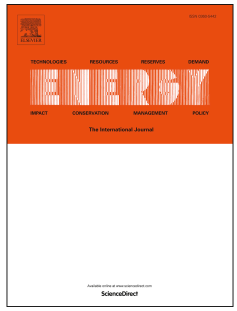

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Do renters skimp on energy efficiency during economic recessions? Evidence from Northeast Scotland

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Abstract

This paper investigates tenants' willingness to pay (WTP) for energy efficiency in the private rented housing sector. Using data from Aberdeen city and Shire in Scotland between the third quarter of 2013 and the second quarter of 2017, rent premiums of 2-11% associated with more energy efficient dwellings are found, and the magnitudes of these premiums are considerable compared to those of other physical attributes. Such premiums however, are significantly reduced during economic recession, suggesting that tenants' WTP for energy efficiency varies under different economic conditions. From a methodological perspective, the study uses a multilevel model, where the unobservable neighbourhood and age effects are approximated. Our results implicate that although tenants' WTP for more energy efficient is present, there still might be a need for public strategy to facilitate the improvement of energy performance in the private rented sector.

Keywords: energy efficiency, split-incentives, private rented housing sector, rent premium, tenants willingness to pay, economic recess

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1. Background

Targets were set by the Climate Change (Scotland) Act 2009 to reduce greenhouse gas emissions substantially.[1] As greenhouse gas emissions from the housing sector account for around a quarter of Scotland's total emissions (The Scottish Government, 2012b), making homes more energy efficient has been a key focus of the government policy. While new housing constructions are subject to building standards, older buildings in the private sector have no regulatory requirement on their energy efficiency performance. Particularly, the private rented sector (PRS) is often perceived to be the least energy efficient among all tenures in many markets in Europe and North America (Carroll et al., 2016; Kholodilin et al., 2016; Hope and Booth, 2014; Wilkinson and Goodacre, 2002), despite its rapid growth in size and importance (Hope and Booth, 2014).

One of the main hurdles to energy efficiency improvement in the PRS is the landlord-tenant split-incentive problem (Wilkinson and Goodacre, 2002; Barten, 2005; Bird and Hernández, 2012; Gillingham et al., 2012; Wood et al., 2012; Hope and Booth, 2014): landlords have the incentive to supply accommodation at the lowest possible cost, but not necessarily the highest efficiency, as tenants tend to be responsible for energy associated costs. Tenants have the incentive to make their accommodation more energy efficient, however the upfront cost of improvement may be too high and/or the payback period may be too long if renting is only intended for a short term (Bird and Hernández, 2012). It has been argued that landlords often are not able to recoup investments from tenants (Schleich and Gruber, 2008), and tenants' lack of willingness to pay (WTP) is usually a result of market failures due to information asymmetry and uncertainty (Allcott and Greenstone, 2012; Davis, 2011; Levinson and Niemann, 2004; Schleich and Gruber, 2008).

It was generally assumed that tenants were unable to fully assess dwellings' energy efficiency levels due to information asymmetry, thus they were unlikely to offer a rent premium that would fully compensate the landlords' investment in energy improvement. In the last decade however, many European housing markets saw improved information transparency on dwellings' energy performance as a result of the requirement of Energy Performance Certifi-

[1]Targets are set to reduce Scotland's greenhouse gas emission by at least 42% by 2020 and 80% by 2050.

cate (EPC)[2]. Wood et al. (2012) suggest that with well-informed tenants and sufficient awareness among them, landlords with more energy efficient buildings should capture a rent premium, which should offset any split-incentive effect. Another factor that influences households' WTP for energy efficiency is uncertainty. Hassett and Metcalf (1993) find that households may apply a high discount rate to future energy savings if there is uncertainty over future conservation savings. Uncertainty could also be related to potential changes in energy prices; or/and it could be a result of the relatively short rental relationship (Kholodilin et al., 2016).

Empirically, a number of studies (Chegut et al., 2013; Eichholtz et al., 2010; Fuerst et al., 2013; Fuerst and McAllister, 2011a,b; Kok and Jennen, 2012; Wiley et al., 2010; Pivo and Fisher, 2010; Reichardt et al., 2012) find significant rent premiums associated with energy efficiency, suggesting that there is a degree of WTP for energy efficient buildings in a number of commercial real estate markets. Gabe and Rehm (2014) and Fuerst and McAllister (2011c) on the other hand, show no rent premiums in the commercial real estate sector. Empirical evidence on the PRS is scarce. Kholodilin et al. (2016) find statistically significant WTP in the Berlin PRS, the magnitude of such WTP however is very small. Hyland et al. (2013) also show that energy efficiency has a positive effect on rental prices of properties in the Irish housing markets. However, arguably the study has little control over dwelling quality and location specifics. Using a Discrete Choice Experiment, Carroll et al. (2016) suggest that renters value energy efficiency. Particularly, the WTP for efficiency improvements is considerably higher at the lower end of the efficiency scale.

Notably, most of these studies use data with a relatively short time frame, and those that cover a longer time period do not consider the potential effects of market conditions, with the exception of Hyland et al. (2013), where the authors find stronger effect of energy rating in the rental market when market conditions are worse. The authors however do not provide further explanation to the findings, and it is unclear whether these differences in WTP are statistically significant. On the contrary, Wilkinson and Goodacre (2002) argue that market conditions are unlikely to play an important role:

[2]In Scotland, since January 2009 all private landlords are required to provide EPC when lease to a new tenant under the Under the Energy Performance of Building (Scotland) Regulations 2008.

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if the demand for rented properties is high, landlords are likely to obtain high rental income regardless whether or not they spend on improvement. If the demand is low, landlords may lose out by charging higher rent related to the more energy efficient improvements. The split-incentive problem is therefore likely to be present regardless market conditions. These studies raise further questions regarding the split-incentive issue in the PRS, thus more evidence is needed to analyse tenants' WTP for energy efficient buildings in the private sector.

Studies in psychology, cognitive science and experimental economics have shown that when feeling stressed, distracted and under pressure or scarcity (financial, emotional, time, etc.), people make decisions differently (Loewenstein, 2000; Kenrick et al., 2009). For example, low-income households are more likely to take out short-term loans with prohibitively high interest rate to pay off immediate daily expenses (Bair, 2005); people facing immediate deadlines tend to only think of the task at hand (Karau and Kelly, 1992); in economic recession, people from a low socio-economic background tend to be more short-term minded and prefer to spend now than to invest in the future (Griskevicius et al., 2013). Overall, research has shown that scarcity impairs people's cognitive capacity to make calculated rational decisions, but frames their mind in the context where the source of stress or distraction is salient. Thus, they tend to focus on the pressing issues while ignoring others (Shah et al., 2012, 2015). Studies also find that during recent economic recession, consumers bypass expensive eco-products such as hybrid cars[3] or trade down to cheaper alternatives (Flatters and Willmott, 2009); and economic issues replace environmental issue as more immediate concerns for consumers (Downs, 1972; Lipsey, 1977; Corrado and Ross, 1990; Kalafatis et al., 1999).

In the light of above, we argue that during stressful times, tenants are likely to focus on the immediate needs and ignore the potential payoffs in the future, thus their demand for energy efficient buildings is likely to decrease relative to other more immediate requirements of housing, such as the necessary space needed.[4] Instead of paying a premium for energy efficiency, they may save energy costs through other channels (such as heating one room rather than the whole property; or wearing more layers of clothing). In addi-

[3]Hybrid cars draw a close parallel to more energy efficient properties: they seem to cost a premium, but will save users on fuel/energy bill in the long run.

[4]For example, the need for (minimum) space needs to be addressed regardless if the household is in stressful condition.

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tion, the higher level of uncertainty during economic downturn would result a higher discount rate applied to the future energy savings. Renters also have the advantage to change their residences relatively easily, therefore can respond more quickly to changes in economic and employment conditions.

Based on this, this paper first examines whether a rent premium for energy efficient dwelling is present. We then test the hypothesis that renters' WTP for energy efficient dwellings reduces during economic recession. The paper also highlights whether the WTP for other housing attributes differs during economic downturns to demonstrate the potential differences between energy efficiency and other housing attributes. Transaction data in the PRS of Aberdeen city and Shire in Scotland is applied to test the hypotheses. The region provides an appropriate case study area, as its housing market performance fluctuated dramatically in the last five years as a result of the peak of oil price in 2013 and the subsequent fall in 2014.

2. Case study area

Located in the northeast of Scotland, Aberdeen city and Shire are the home to more than 400,000 residents. Due to its proximity to the North Sea oil fields, the region is also a hub for many large oil and gas companies and their supporting services, thus earns its name as the "Europe's oil capital". The local economy is heavily reliant on the oil and gas sector: it accounts for more than 20% of the employment and more than half of the total turnover (Aberdeen City Council, 2015). As a result of the recent turmoil in oil prices, Aberdeen has suffered substantial job losses from the energy sector (Ambrose, 2016). For those fortunate enough to keep their jobs, the level of pay and benefit is no comparison to the pre-crises level (Chester, 2016).The downturn in the gas and oil sector has inevitably affected other sectors in the region, especially the private housing market. Mortgage arrears doubled the national level in 2016 (Ambrose, 2016), and as illustrated in Figure 1, both rental and price level saw a significant decline from 2014Q3, a few months lagging behind the start of the oil price slump. Notably, the CPI index of electricity, gas and misc only shows a slight decrease since 2014Q3, suggesting that there has been little change in energy price for consumers. Thus any change in tenants' WTP for energy efficient buildings is unlikely to be a direct result of the small changes in energy price.

[Insert Figure 1 here]

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3. Data

Transaction data of private residential property leases from the Aberdeen Solicitors Property Centre (ASPC) was obtained on the basis of a non-disclosure agreement between the University of Aberdeen and the ASPC. The datasets record properties marketed as "to let" in the housing market area defined by the local authorities in Aberdeen and Aberdeenshire (see Figure 2) from 1985Q3 to date (2017Q3).

[Insert Figure 2 here]

Due to the availability of EPC ratings (details see Section 3.2), lease data includes 13,197 properties advertised through the centre between the second quarter of 2013 and the third quarter of 2017. The dataset includes information on the listing date and leased date of each property and achieved rent. Physical attributes such as property type, number of public rooms, number of bedrooms, whether the property has central heating, garden and garage(s) are available in the dataset. Locational attributes are also included (details see Section 3.1). The variables used for the analysis are listed in Table 1, and the summary statistics of the lease data variables are presented in Table 2. Notably, year quarter dummies have less observations, as some properties were still on the market at the time of this analysis. Variable *rent* also has less observations due to the fact that over 3,600 properties were withdrawn from the listing.

[Insert Table 1, 2 here]

One major advantage of the ASPC lease dataset is that both asking rent and achieved rent are recorded. Achieved rent is used to evaluate tenants' WTP for energy efficient buildings. This can avoid the potential problems associated with using estimated market rent or asking rents highlighted by Gabe and Rehm (2014) - such variables measure expectations but not the outcomes (WTP). The data also shows that since 2014Q3, there were an increasing number of properties that were leased at a price below the asking rent, and the proportion of withdrawn properties also increased substantially from a few dozens in a quarter to a few hundreds in a quarter. This further illustrates the severity of the economic impact on the RPS.

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Because the ASPC only captures rented properties when they are advertised through the centre[5], the observations in the dataset only consist of a sub-sample of the total RPS stock in Aberdeen city and Shire[6]. We do not anticipate sample size issues, other studies on the PRS, such as the rent trend study by The Scottish Government (2015), use samples of similar size for Aberdeen area.

3.1. Spatial variables and potential omitted variable problems

One advantage of the ASPC data is that it includes multiple measures of location. This allows us to carry out a number of spatial controls in the hedonic regression models to avoid the potential bias in the estimation of the effect of energy efficiency measures in the absence of such control. For example, in Fuerst and McAllister (2011a), there was no specific control for the location of each property within the region. As a result, the authors suggest that "*a mere location price effect may be erroneously attributed to energy performance*" (page. 6611), if buildings with different levels of energy performance are not randomly distributed spatially.

Another concern of using hedonic models is the potential bias caused by the omitted variables. One variable that would be closely related to the EPC rating but not available in our dataset is the age of the property. To address this issue, we allow potential age effect to be reflected at a higher level within each full 7-digit *Postcodes*[7], based on the assumption that dwellings with the same postcode are very likely to be constructed during the same time period.[8] In addition, the dataset has a dummy variable *Newbuild* to indicate whether a property is newly constructed, which allows further control for age.

3.2. EPC ratings

As mentioned earlier, since January 2009, all private landlords are required to provide an EPC when leasing their properties to a new tenant under the Energy Performance of Building (Scotland) Regulations 2008. Since

[5]These are listings through estate agents that are often operated by solicitors. Leasing through other channels (such as Gumtree) are not captured by the ASPC.

[6]It is estimated by the local authorities that around 14,000 households in Aberdeen city and 10,000 in Aberdeenshire lived in private rented accommodation in 2015.

[7]On average, there are 15 properties in each postcode, we allow random effect at postcode level, and this is discussed in detail in section 4.

[8]As new developments or the conversion of existing premises may result in the need for new postal addresses.

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our analysis uses data from 2013, we do not have the sample selection issue raised in other papers.[9]

An EPC report contains information about the property's energy use, its typical energy costs and recommendations about how to reduce energy use. The certificate also gives the property an energy efficiency rating from A (most efficient) to G (least efficient). An EPC can only be produced by an expert who needs to be a member of an approved Government Accreditation scheme. The assessor collects energy related features[10] during the inspection, and the data is analysed by computer software developed by the government. The rating system uses information on the performance of the building itself such as heating and lighting, therefore provides an energy efficiency rating for the property itself rather than depending on the occupier. The ASPC data started to record EPC ratings from the third quarter of 2013 for most properties.[11]

The Scottish House Condition Survey shows that 40% of dwellings in the sample had an EPC between A and C, 40% had an EPC D, and 20% below D in 2010.[12] The ASPC data shows similar proportions: a slightly higher proportion (43%) of leased properties rated C and above, 33% of properties had an EPC D, and 24% below D (See Table 2).

4. Models

In line with existing studies (Eichholtz et al., 2010; Brounen and Kok, 2011; Fuerst et al., 2013), we use hedonic regressions to examine the relations between rents and energy performance. There are four specifications for the models used in this study. The first specification is a baseline log-linear hedonic model (Model 1) which is presented in Eq. 1:

$$\log(\textsc{Rent}_i) = \alpha_i + \beta X_i + \gamma Geocode_i + \epsilon_i \;, \tag{1}$$

[9]In a market where energy efficiency measures are not mandatory, or if the owners do not have to provide EPC or equivalents when advertising, it is possible that the data is subject to selection bias (Carroll et al., 2016; Hyland et al., 2013; Kholodilin et al., 2016).

[10]This typically include information on property type, age, type of construction, property dimensions, room and water heating systems, insulation levels, windows and glazing types, and types of lighting.

[11]Missing values are due to errors in data recording.

[12]The results are presented in The Scottish Government (2012a), housing tenure is not differentiated in the report.

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where $\log(\text{RENT}_i)$ is the natural logarithm of the realised annual rent for property i. X_i is a vector of the explanatory variables for the property attributes, including $Numpublic$, $Numbedrooms$, $Numbathrooms$, $Heating$, $Cloakroom$, $Garage$, $Garden$, $Parking$, $Newbuild$, TOM, $Furnish$, $NondeMulti$, $NondeSing$, $DetaMulti$, $DetaSing$, $FlatMulti$, $FlatSing$, $Year\ Quarter$ (see Table 1 for variable names and their descriptions). β is a vector of parameters to be estimated for the physical attributes. To control for the location of properties, $Geocode_i$ is included. It consists of the standardised[13] spatial coordinates and their cross products. Specifically, these are x, $x^2, ..., x^5$, y, $y^2, ..., y^5$, xy, xy^2,..., xy^5. The inclusion of the geographic coordinates is to smooth the unobservable geographic differences of properties (Jackson, 1979; Bracke, 2015; Bracke et al., 2017). Further discussion of this spatial specification and robustness test results are presented in Appendix. ϵ_i is the random error which is the stochastic disturbance term from a normal distribution of $N(0, \sigma^2)$.

In Model 2 (Eq. 2), the EPC binary variables are included to indicate the energy performance of the property. If the estimated coefficients are statistically significant, the model then captures rental premiums associated with energy performance.[14]

$$\log(\text{RENT}_i) = \alpha_i + \beta X_i + \gamma Geocode_i + \delta EPC_i + \epsilon_i \ . \qquad (2)$$

Fuerst and McAllister (2011c) suggest that the estimated coefficients of the EPC ratings may be dependent on which EPC rating variables are omitted in regression (in our regression models, we omitted EPC E), thus sensitivity tests are conducted using different reference EPC rating variables.[15]

To take into account the local economic crisis (as shown in the third quarter of 2014 in Figure 1), a structural break of 2014Q3 is included in the analysis. Particularly, dummy variable 2014Q3 is interacted with all physical attribute measures and EPC binary variables, and these interactive terms are included in Model 3 (Eq. 3). If the estimated interactive coefficients are

[13]The derivation from its mean, divided by its standard derivation: $\dfrac{lat - \mu_{lat}}{\sigma_{lat}}$, $\dfrac{lng - \mu_{lng}}{\sigma_{lng}}$.

[14]Due to small sample size, EPC A is combined with B as one rating. E is chosen as the reference rating.

[15]The results are available from authors upon request.

statistically significant, the model then captures the additional changes of rental premium associated with housing characteristics and energy performance after the break.

$$\log(\textsc{Rent}_i) = \alpha_i + \beta X_i + \gamma Geocode_i + \delta EPC_i + \tau[Break \times X_i] + \eta[Break \times EPC_i] + \epsilon_i \ . \quad (3)$$

where $Break$ is an indicative variable for the oil crisis break, specified as 1 after 2014Q3 and 0 otherwise.[16] τ and η denote the coefficients on physical attributes and energy efficiency ratings during economic downturn, respectively.

As mentioned previously, information on dwelling age is not completely available in the ASPC dataset, and full postcodes are used in this study to control for dwelling age based on the assumption that dwellings in the same postcodes were developed around the same time. One could argue that there may be differences in rents within each postcode due to the (unobserved) differences in the age of the dwellings as well as the neighbourhood effects embedded each postcode. Neighbourhood effect could be a result of school quality, the provision of amenities, households' characteristics such as income, education and employment, and so on. This effect may cause price variation in the housing market, but is difficult to observe/quantify. Bracke et al. (2017) allow fixed effect at street level to disentangle neighbourhood effect from other features. We allow similar control at postcode level. In other words, each postcode, j, may have a different intercept term α_j. Further, the implicit price of a particular housing attribute expressed in Model 2, may vary among the postcodes. Therefore, following Gelfand et al. (2007), Orford (2002) and Liu and Roberts (2012), the following multilevel model is estimated for each of the postcode:

$$\log(\textsc{Rent}_{i,j}) = \alpha_j + \sum \theta_k Z_{k,i,j} + [\mu_{\alpha,j} + \mu_{\beta,k,j} + \epsilon_{i,j}] \ , \quad (4)$$

where
$i = 1, 2, ..., n$ properties (level one of the multilevel model);
$j = 1, 2, ..., n$ postcodes (level two of the multilevel model with properties

[16]The break is identified ex post and tested by Chow test on rental index and crude oil price index. A number of break points between 2014Q3 and 2015Q2 were also trialled for the analysis, based on structural breaks in the average TOM (time on the market - see Table 1), and the sudden increase in the number of withdrawn properties. Empirical results are very similar to that of applying 2014Q3 as the structural break.

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nested within each postcode);
$k = 1, 2, ..., n$ attributes.

For simplicity, $Z_{k,i,j}$ denotes all housing structural and locational attributes, and break interactive terms (a combination of X, Geocode, EPC and interactive variables in Eq. 3).

The model in Eq. 4 allows for the existence of both random intercept effects and random slope effects. In particular,

$$\alpha_j = \alpha + \mu_{\alpha,j} \ ,$$

where α_j is the average constant for postcode j, and is a function of the average constant across the postcodes plus a varying difference $\mu_{\alpha,j}$ for each postcode. Similarly,

$$\beta_{k,j} = \beta + \mu_{\beta,k,j} \ ,$$

indicating for each individual coefficient, the slope term is seen as an average slope at postcode level plus a variation from postcode to postcode. The bracketed term in Eq. 4 captures the random elements.

The relationship between the two types of random effects can be further explored by creating a correlation:

$$corr(\mu_{\alpha,j}, \mu_{\beta,k,j}) = \frac{cov(\mu_{\alpha,j}, \mu_{\beta,k,j})}{\sigma_{\mu_{\alpha,j}} \sigma_{\mu_{\beta,k,j}}}$$

The model 4 contains four random disturbance: σ_ϵ for level one which is the individual property level. $\sigma_{\mu_{\alpha,j}}$, $\sigma_{\mu_{\beta,k,j}}$, and $cov(\mu_{\alpha,j}, \mu_{\beta,k,j})$ for level two postcode level. We also carry out some robustness tests with regard to location measures in the model, these are included the Appendix.

The ASPC data is then applied to all four models and results are presented in the next section.

5. Results

Table 3, 4 and 5 show hedonic regression results for rents under each model specification. All models have an explanatory power of around 80%. In Model 1, most of the estimated effects of house attributes on rent are as expected (for example, an additional public room, a bedroom, a cloak room or a bathroom yields significantly positive coefficients on annual rents), and the geographic coordinates also show significant effects in smoothing the

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unobservable geographic differences of properties.[17] However, the negative effect of detached type of properties, compared to non-detached properties, and the positive coefficient of TOM are difficult to interpret. Time dummy variables as control for market conditions show some level of fluctuations in rental level over the time period.

[Insert Table 3, 4 and 5 here]

Model 2 includes EPC ratings, and the results on physical, locational and market condition measures are very consistent with those in Model 1, apart from a noticeable reduction in the magnitude of "Newbuild", suggesting that without the measures of EPC ratings, it is difficult to distinguish the effects of energy efficiency of being a new dwelling from other perceived quality associated with the variable. Regarding the coefficients of EPC ratings in Model 2, rent premiums and discounts are found to be present. For example, compared with an E rated property (the default), A/B rated properties are leased at a premium of 8%, and C rated properties have a premium of 1.6%. Less energy efficient buildings such as those with G ratings were leased at a discount. There are no statistical differences in rents between E and D rated buildings and E and F ratings.

The coefficients of the interactive variables are highlighted in Model 3 and Model 4. Because Model 4 allows further control of dwelling age and neighbourhood effects at postcode level (indicated by the significant σ and χ_2 statistics), this further confirms the presence of such hierarchical structure within the housing market. Our discussion here focuses on the results from model 4. With regard to the physical attributes, most characteristics yield similar coefficients as in Model 2. Notably, the effect of TOM is no longer positive, but also statistically insignificant. Furnished properties yield much larger coefficient in Model 4, and there is little difference among rental levels with regard to dwelling type.

Turning attention to the magnitudes and significance of the EPC variables, some coefficients of EPC ratings in Model 4 are larger and more statistically significant compared to those in Model 2, confirming the need for allowing control for age and neighbourhood effect. Given the average annual rent of £9832 in our sample, the associated rent increase for upgrading from

[17] Most coefficients of spatial coordinates and their higher orders are statistically significant at 1%, they can be provided upon request.

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E rating to D is £295 per annum, and £393 and £737 per annum respectively for upgrading to C rating or A/B rating. To put this in perspective, we investigate EPC reports of current two bedroom properties that on the market. Typically, a property of EPC E that has the potential to upgrade to C would save around £400 per annum on heating alone (based on gas central heating). Discounts on F and G rated properties are also present and statistically significant at 2.7% and 6.8% respectively. These premiums/discounts are of similar size to the findings in Carroll et al. (2016). The premiums/discounts are also progressive, suggesting that the market is able to distinguish between the different level of EPC ratings, so an upgrade of the property energy performance at any level would be rewarded with a rent premium. It is also notable that compared to other attributes of the property, the effect of energy efficiency on rent is non-trivial.

One could argue that WTP for energy efficiency might be sensitive to dwelling sizes - with small dwellings, renters are less sensitive to energy performance than renters of larger dwellings, where the energy cost could be relatively large. To further test this, we included a further dummy variable - *Large* in Model 4, to indicate larger properties with four and more than four bedrooms[18], and *Large* is subsequently interacted with EPC ratings. The result is presented in Appendix Table A.7. It shows that most of the interactive terms yield insignificant coefficients but $Large \times EPCD$. This suggests that tenants of larger properties are not more sensitive to energy performance than tenants of smaller properties in our sample.

To see the potential market condition effect, the coefficients of the EPC ratings should be interpreted along with the interactive terms in Model 4. For example, compared to EPC E rating, rent premiums saw 3%, 2%, and 1.6 %[19] reduction for A/B, C, and D rated properties respectively since 2014Q3. In other words, compared to properties with an EPC rating of E, rental premiums are smaller for D and above rated properties in economic downturn, whereas the discounts for lower rated properties remain unchanged. These results are opposite to the findings in Hyland et al. (2013), but confirm our hypothesis that tenants are less willing to pay for more energy efficient

[18]We also tried three bedrooms as an approximation for larger properties, and the results are very similar to using four bedroom house as an indication of larger properties.

[19]These coefficients are significant at 10% level. Although arguably, this significance is relatively low compared to other coefficients, the results are robust with regard to the choice of structural break point that mentioned in footnote 16.

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buildings during economic downturn (at least for properties with an EPC rating of E or above). In addition, all but one coefficients of the structural break interacted with bedroom and public room variables are statistically insignificant, indicating that tenants' WTP for the necessaries such as the minimum space is not influenced by the economic conditions.

6. Discussion and Conclusion

Split-incentives have been perceived as one of the major hurdles of improving energy performance of dwellings in the PRS. While the existing studies tend to compare energy expenditure between tenants and owner-occupiers to indicate the presence of the issue, we argue that a more direct way to investigate the presence of split-incentive issue is through the study of tenants' WTP for more energy efficient homes. Such WTP could be in the form of rent premium. In the light of psychological studies, this study provides a new conceptualisation of the factors that would influence households' WTP for energy efficient buildings, and considers the potential changes in tenants' behaviours during economic downturn.

Consistent with other studies in the PRS (such as Kholodilin et al. (2016), Hyland et al. (2013) and Carroll et al. (2016)), our empirical results generally show strong evidence of such premiums in the rented sector in northeast Scotland. Our energy efficiency premium however is larger compared to that in other studies: compared to properties with an EPC E, rent premiums range from 2-11% for properties with better energy performance, and a 3-7% discount for properties with lower energy efficiency across four models. The magnitudes of these premiums are considerable in comparison to those of other typical physical attributes. These rent premiums also seem to be substantial relative to typical retrofits costs (for example, an upgrade to new double glazed windows typically costs approximate £1000 each, loft insulation costs between £200-£300 for a typical house, and wall insulation costs around £200). Also, the progressive premium suggests that the market is able to distinguish between different levels of energy performance, so an upgrade of the property at almost any level will be rewarded with a rent premium.

Compared to other studies on WTP in the PRS, our study specifically considers behaviour changes under economic constraints. It is important to highlight that in line with psychological theories, such WTP for energy performance is significantly reduced among E and above rated properties since

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later 2014, when the regional economy suffered from the dramatic downturn in oil price. Our results further confirm that while rent premiums on energy efficiency is reduced, premiums on additional bedrooms and public room remain more or less the same, suggesting that during economic downturn, people indeed focus on necessaries, and may seek alternative ways to save energy cost.

This study confirms that the split-incentives problem is a complex issue: while tenants are generally responsive to EPC ratings, and landlords can potentially reap the benefits from the investment in energy efficiency in rents, they may less be able to do so during economic downturns. Thus although there is little financial reason for under-investment during normal economic conditions, landlords may fear the reduced/lack of WTP for energy efficiency when the market is at trough. In addition, other hurdles related to financial constraints (for example, insufficient lump sum available to carry out the improvements) and/or limited access to credit could also limit landlords' ability to improve energy performance. Moreover, some properties are structurally challenging to be upgraded to a higher EPC level (the "hard to treat" properties). These are important considerations for policy makers when implementing interventions on energy performance of dwellings in the sector. For example, financial incentives may be more appropriate in improving energy performance during economic downturns. Similar suggestions can be found in cleaner car studies, such as Poder and He (2017), where it was suggested that consumers' actual WTP for cleaner cars is unlikely to be sufficient for the development of the market, thus there is a need for a public strategy to facilitate the commercial development of cleaner vehicles.[20]

Finally, in terms of the modeling technique, our models show the importance to allow for hierarchical structure that may be present in the housing data. The benefits of the two level modeling also include allowing approximation of the age and neighbourhood effect that otherwise would be omitted from the analysis.

We also recognise some of the potential shortcomings in this study. In terms of data, some of the characteristics of the dwellings are approximated due to data limitation. While this allows for some control for age and size

[20]Poder and He (2017) further give an example of such strategy - the "bonus-malus" system implemented in France at the beginning of 2008, which subsidised the purchase of environmentally friendly cars and reduced the taxation of these cars substantially as well.

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of the property, they are not precisely measured. For example, we do not observe if a property has recently been renovated even if it might have been an old building. Our further test results on the sensitivity of EPC premiums among large properties compared to smaller dwellings needs further investigation. It might be that energy consumptions are better managed with new technologies (such as smart meters) that dwelling size no longer makes a significant difference. We use number of rooms and dwelling type as a control for property size, but we do not observe the actual size of the property. However, by checking the adverts for recent rented properties on the market, it appears that the room sizes of rented properties do not seem to vary substantially (for example, double bedrooms tend to be around 13 square meters, living rooms tends to be around 16 square meters).

Another limitation is that the status/condition of the building is not indicated in the dataset, although some of the existing variables may capture this to a certain extent, for example, we know whether a property is old or new, furnish or nonfurnished, has central heating or not; the status/condition of the dwellings may play an influential role if can be quantified and included in the model. Because the dataset only shows dwellings that were leased via estate agents (often operated by solicitors), who charge management fees, and properties are maintained regularly; it may be reasonable to assume that dwellings are maintained relatively well (compared to those that are leased directly from landlords, tenants' rights seem to be more protected if renting via established agents).

Our data is unbalanced (1 years pre-crisis and 3 years during crisis), as further stage of the property cycle emerges, we will be able to expand the data to capture such changes in market condition. With regard to the measure of energy performance, there have been debates of the adequacy of EPC, nevertheless it is the mandatory and most available measure for all dwellings in Scotland. From a behaviour perspective, it is possible that properties with higher energy performance are also maintained by more attentive and responsible landlords or home-owners. Such information is not available for our analysis, and we will leave it for future research.

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8. Figures and Tables

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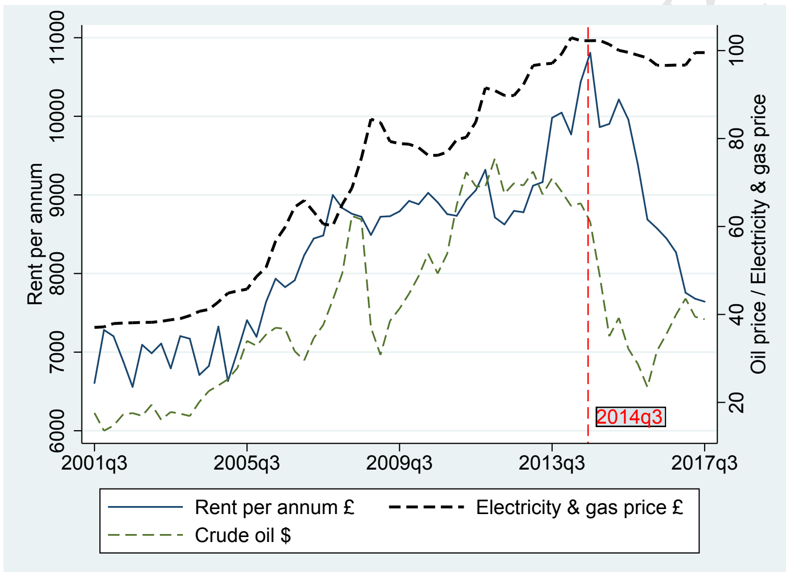
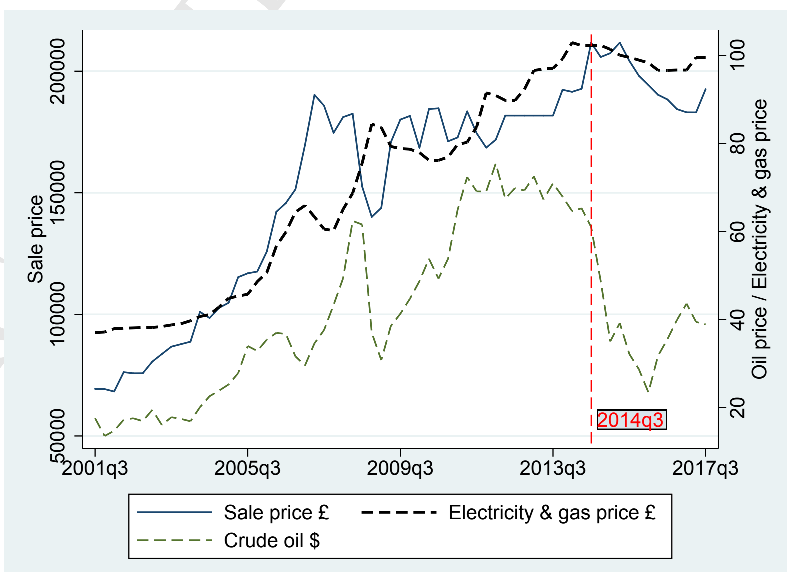
Figure 1: **Aberdeen house price and rent vs. the oil price and the electricity & gas price:** The rent and sale price are the cross-sectional average of all properties. The oil price is the crude oil price in dollars. The electricity and gas price is the UK CPI index of electricity, gas and misc. energy in pounds. Both oil price and electricity & gas price are quoted from Datastream.



(a)



(b)

Figure 2: Housing Market Areas Aberdeen city and Aberdeenshire

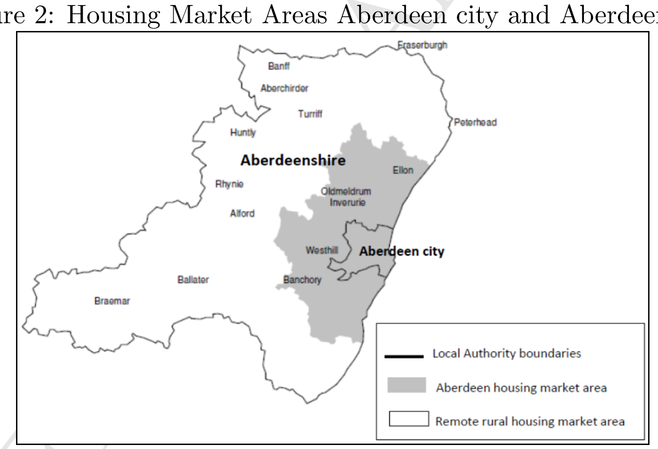


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Table 1: Descriptions of variables that are included in the hedonic model

Variable Name	**Description**
hline *Rent*	Achieved annual rent of the property
x	Spatial coordinate (latitude) of the property after standardisation
$x^2 - x^5$	Higher orders (from 2 to 5) of the standardised latitude of the property
y	Spatial coordinate (longitudes) of the property after standardisation
$y^2 - y^5$	Higher orders (from 2 to 5) of the standardised longitude of the property
$xy - x^5y$	Products of higher orders (from 2 to 5) of standardised latitude and longitude of the property
Postcode	Full postcode of the property
Zone	Intermediate Zone of the property
Numpublic	Number of public rooms (0, 1, 2, 3, 4 or more than 4); including lounge, living room, drawing room, family room, kitchen, etc. A studio flat has 0 public rooms
Numbedrooms	Number of bedrooms (0, 1, 2, 3, 4 or more than 4), a studio flat has 0 bedrooms
Numbathrooms	Number of bathrooms (0 to 5). 0 indicates shower-room(s)
Heating	A binary variable to indicate whether the property has central heating
Cloakroom	A binary variable to indicate whether the property has cloakroom(s)
Garage	A binary variable to indicate whether the property has garage(s)
Garden	A binary variable to indicate whether the property has garden(s)
Parking	A binary variable to indicate whether the property has a driveway or on street parking
Newbuild	A binary variable to indicate whether the property is newly constructed
TOM	Time on the market in weeks, computed as the duration between the listing date and sold/leased date
NondeMulti	A binary variable to indicate whether the property is a non-detached house with more than one floor (baseline)
NondeSing	A binary variable to indicate whether the property is a non-detached bungalow
DetaMulti	A binary variable to indicate whether the property is a detached house with more than one floor
DetaSing	A binary variable to indicate whether the property is a detached bungalow
FlatTop	A binary variable to indicate whether the property is a top floor flat
FlatMid	A binary variable to indicate whether a flatted property is between ground floor and top floor
FlatGroud	A binary variable to indicate whether the property is a ground floor flat
Furnish	A binary variable to indicate whether the property is fully or partly furnished
Year Quarter	A categorical variable of sale year and quarter, 2013Q3 as the reference year and quarter
EPC_A − *EPC_G*	Binary variables to indicate the EPC Rating of the property (*EPC_E* as the baseline, *EPC_N* as missing EPC rating)
$Break_2 014Q3$	A binary variable to indicate whether the property rented during & after 2014Q3

Table 2: Descriptive statistics of variables for private residential leases rental data from ASPC during 2013Q3 to 2017Q3.

Variable	Obs	Mean or %	Std. Dev.	Min	Max
Annual Rent	9531	9832.37	4017.18	3000	53400
Numpublic	13197	1.25	0.59	0	6
Numbedrooms	13197	2.21	1.06	0	7
Numbathrooms	13197	1.27	0.55	0	7
Heating	13197	86.82%	33.83%	0	1
Cloakrm	13197	11.93%	32.42%	0	1
Garage	13197	21.32%	40.96%	0	1
Garden	13197	45.03%	49.75%	0	1
Parking	13197	65.12%	47.66%	0	1
Newbuild	13197	1.20%	10.91%	0	1
TOM	12282	8.22	14.53	0	614.29
Furnish	13197	60.19%	48.95%	0	1
DetaSing	13197	4.83%	21.45%	0	1
DetaMulti	13197	11.84%	32.30%	0	1
NondeSing	13197	3.64%	18.72%	0	1
NondeMulti	13197	14.98%	35.69%	0	1
FlatGround	13197	21.44%	41.04%	0	1
FlatMid	13197	28.56%	45.17%	0	1
FlatTop	13197	12.11%	32.62%	0	1
2013Q3	12282	4.40%	20.50%	0	1
2013Q4	12282	3.62%	18.69%	0	1
2014Q1	12282	3.73%	18.95%	0	1
2014Q2	12282	3.82%	19.17%	0	1
2014Q3	12282	4.35%	20.39%	0	1
2014Q4	12282	2.12%	14.40%	0	1
2015Q1	12282	3.49%	18.36%	0	1
2015Q2	12282	5.07%	21.94%	0	1
2015Q3	12282	7.25%	25.93%	0	1
2015Q4	12282	7.44%	26.25%	0	1
2016Q1	12282	8.44%	27.79%	0	1
2016Q2	12282	8.42%	27.77%	0	1
2016Q3	12282	10.93%	31.21%	0	1
2016Q4	12282	8.33%	27.63%	0	1
2017Q1	12282	8.52%	27.93%	0	1
2017Q2	12282	9.30%	29.04%	0	1
2017Q3	12282	0.77%	8.76%	0	1
EPC_A	13197	0.04%	1.95%	0	1
EPC_B	13197	6.98%	25.48%	0	1
EPC_C	13197	35.07%	47.72%	0	1
EPC_D	13197	33.14%	47.07%	0	1
EPC_E	13197	15.37%	36.07%	0	1
EPC_F	13197	6.75%	25.09%	0	1
EPC_G	13197	1.93%	13.77%	0	1
EPC_N*	13197	0.72%	8.45%	0	1
Latitude	13196	57.1689	0.1878	51.0132	57.7046
Longitude	13196	-2.2029	0.1993	-3.4014	-0.9434
Break_2014Q3	13197	85.51%	35.20%	0	1

* EPC_N denotes EPC rating is missing

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Table 3: Hedonic regression results of four forms in Eq. 2, 3, 4 for private residential leases rental data from ASPC during 2013Q3 to 2017Q3, part I.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Heating	0.0601***	0.0500***	0.0333***	0.0296***
	(11.90)	(9.71)	(2.60)	(2.79)
Cloakrm	0.0413***	0.0344***	0.0515***	0.0561***
	(6.61)	(5.49)	(3.43)	(4.16)
Garage	0.0222***	0.0225***	0.0374***	0.0430***
	(4.27)	(4.33)	(2.97)	(3.86)
Garden	0.0239***	0.0265***	0.0279**	0.0239**
	(5.28)	(5.82)	(2.51)	(2.56)
Parking	0.0517***	0.0427***	0.0395***	0.0297***
	(13.77)	(11.08)	(4.53)	(3.99)
Newbuild	0.121***	0.0845***	0.0563*	0.0438
	(8.58)	(5.84)	(1.69)	(1.63)
TOM	0.000733***	0.000950***	0.00150	-0.00192
	(2.80)	(3.34)	(0.25)	(-0.39)
Furnish	0.0395***	0.0391***	0.0923***	0.0845***
	(9.35)	(9.29)	(10.47)	(11.36)
DetaSing	-0.000314	0.0107	-0.00107	-0.00233
	(-0.04)	(1.27)	(-0.06)	(-0.14)
DetaMulti	-0.0169**	-0.0108	-0.0250	-0.00245
	(-2.24)	(-1.43)	(-1.40)	(-0.15)
NondeSing	0.0297***	0.0314***	-0.00592	0.00513
	(3.31)	(3.52)	(-0.29)	(0.29)
FlatGround	-0.0111*	-0.0155**	0.0276*	0.00712
	(-1.77)	(-2.47)	(1.83)	(0.55)
FlatMid	-0.00554	-0.0175***	0.0333**	0.0170
	(-0.89)	(-2.80)	(2.18)	(1.31)
FlatTop	-0.0213***	-0.0236***	0.0302*	0.0194
	(-2.88)	(-3.20)	(1.69)	(1.30)
EPC_AB		0.0796***	0.110***	0.0750***
		(9.60)	(5.59)	(4.73)
EPC_C		0.0160***	0.0347***	0.0402***
		(3.00)	(2.75)	(3.91)
EPC_D		0.00767	0.0291**	0.0300***
		(1.51)	(2.44)	(3.10)
EPC_F		-0.00687	-0.0266	-0.0267*
		(-0.91)	(-1.58)	(-1.88)
EPC_G		-0.0723***	-0.0695**	-0.0684***
		(-5.59)	(-2.44)	(-2.81)
α	8.637***	8.671***	8.531***	8.682***
	(75.60)	(74.11)	(33.49)	(34.13)
Year Quarter Vars	$\surd$	$\surd$	$\surd$	$\surd$
Coordinates Vars	$\surd$	$\surd$	$\surd$	$\surd$
Multilevel 2-level				$\surd$
Interactive 2014Q3			$\surd$	$\surd$
Observations	9530	9461	9461	9451
R squared	79.51%	79.94%	80.75%	81.09%(1),82.80%(2)
Random Effect Parameters				
Level 1 property σ				0.1097***
Level 2 postcode σ				0.1184***
Likelihood ratio χ^2				2194.55***

t-statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

R^2 for 2-level regression is Snijders/Bosker R-squared.

Bryk/Raudenbush R-squared for 2-level regression is 67.48% for level 1, and 86.09% for level 2.

Table 4: Continues from previous page of Table 3, hedonic regression results of four forms in Eq. 2, 3, 4 for private residential leases rental data from ASPC during 2013Q3 to 2017Q3, part II.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Numpublic1	0.0756***	0.0630**	0.0502	0.0644*
Numpublic2	0.130***	0.121***	0.120***	0.120***
Numpublic3	0.210***	0.201***	0.259***	0.241***
Numpublic4	0.293***	0.288***	0.263***	0.264***
Numpublic5	0.372***	0.367***	0.827***	0.769***
Numbedrooms1	0.281***	0.256***	0.267***	0.206***
Numbedrooms2	0.534***	0.507***	0.544***	0.464***
Numbedrooms3	0.689***	0.665***	0.722***	0.640***
Numbedrooms4	0.807***	0.786***	0.890***	0.817***
Numbedrooms5	0.925***	0.902***	1.015***	0.962***
Numbedrooms6	1.066***	1.042***	1.362***	1.202***
Numbedrooms7	0.966***	0.941***	1.132***	1.074***
Numbathrooms1	-0.0573	-0.0469	0.0455	-0.0123
Numbathrooms2	0.0852	0.0840	0.189*	0.100
Numbathrooms3	0.140	0.134	0.231**	0.190**
Numbathrooms4	0.256***	0.249***	0.218	0.107
Numbathrooms5	0.322***	0.325***	0.220	0.252
Numbathrooms6	0.139	0.126	0.154	0.115
2013Q3	-0.0494***	-0.0458***	-0.156	-0.142
2013Q4	-0.0627***	-0.0630***	-0.175	-0.147
2014Q1	-0.0657***	-0.0691***	-0.177	-0.147
2014Q2	-0.0194*	-0.0216**	-0.136	-0.116
2014Q4	-0.0261**	-0.0237*	-0.0275**	-0.0218**
2015Q1	-0.0286***	-0.0296***	-0.0334***	-0.0350***
2015Q2	-0.0476***	-0.0517***	-0.0531***	-0.0512***
2015Q3	-0.0718***	-0.0732***	-0.0726***	-0.0690***
2015Q4	-0.145***	-0.147***	-0.150***	-0.147***
2016Q1	-0.203***	-0.204***	-0.205***	-0.204***
2016Q2	-0.224***	-0.226***	-0.228***	-0.232***
2016Q3	-0.253***	-0.255***	-0.256***	-0.256***
2016Q4	-0.290***	-0.293***	-0.296***	-0.301***
2017Q1	-0.324***	-0.327***	-0.328***	-0.328***
2017Q2	-0.306***	-0.309***	-0.312***	-0.316***
2017Q3	-0.292***	-0.295***	-0.297***	-0.319***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Table 5: Continues from previous two pages of Table 3, hedonic regression results of four forms in Eq. 2, 3, 4 for private residential leases rental data from ASPC during 2013Q3 to 2017Q3, part III.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Break×Numpublic1			0.0189	-0.0328
Break×Numpublic2			0.00458	-0.0485
Break×Numpublic3			-0.0690	-0.115**
Break×Numpublic4			0.0320	-0.0531
Break×Numpublic5			-0.556***	-0.588***
Break×Numbedrooms1			0.244	0.257
Break×Numbedrooms2			0.210	0.225
Break×Numbedrooms3			0.183	0.211
Break×Numbedrooms4			0.123	0.160
Break×Numbedrooms5			0.105	0.122
Break×Numbedrooms6			-0.152	0.0259
Break×Numbathrooms1			-0.226	-0.168
Break×Numbathrooms2			-0.236	-0.197
Break×Numbathrooms3			-0.218	-0.213
Break×Numbathrooms4			-0.0652	0.0152
Break×Heating			0.0202	0.00764
Break×Cloakrm			-0.0188	-0.0145
Break×Garage			-0.0204	-0.0259**
Break×Garden			-0.00166	0.00456
Break×Parking			0.00161	-0.00433
Break×Newbuild			0.0358	0.00963
Break×Furnish			-0.0678***	-0.0631***
Break×DetaSing			0.0162	0.0312*
Break×DetaMulti			0.0170	0.0244
Break×NondeSing			0.0487**	0.0354*
Break×FlatGround			-0.0540***	-0.0454***
Break×FlatMid			-0.0626***	-0.0495***
Break×FlatTop			-0.0662***	-0.0544***
Break×EPC_AB			-0.0389*	-0.0296*
			(-1.80)	(-1.74)
Break×EPC_C			-0.0227	-0.0195*
			(-1.64)	(-1.77)
Break×EPC_D			-0.0251*	-0.0160*
			(-1.91)	(-1.65)
Break×EPC_F			0.0277	0.0244
			(1.47)	(1.59)
Break×EPC_G			-0.00591	-0.0138
			(-0.19)	(-0.53)

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Appendix A. Robustness Check

We also utilise spatial autoregressive model (Anselin, 1998; LeSage and Pace, 2010) to account for the decaying influence of recent transaction with distance. The spatial autoregressive model (Model 6) is defined as Eq.A.1:

$$\log(\text{Price}_i) = \alpha_i + \rho W_{i,j} \log(\text{Price}_j)_{t-h} + \beta X_i + \delta EPC_i + \tau[Break \times X_i] + \eta[Break \times EPC_i] + \epsilon_i \ , \tag{A.1}$$

where $W_{i,j}$ is the spatial weighting matrix (usually a first-order contiguity matrix) between property i and j and $i \neq j$, ρ is the coefficient of spatially lagged dependent variable, and h is the number of lags. We generate the spatial weight matrices using k-nearest neighbor weight, radial distance, power distance, exponential distance, and double-power distance approach, based on the Haversine distance matrix computed from the latitude and longitude of each property. We choose k-nearest neighbor weight over others for providing the highest explanatory power.

Fuerst and McAllister (2011a) and Eichholtz et al. (2010) find the results of regression procedure can be sensitive to the outliers caused by faulty data, i.e. some prices or rents may appear to be too low/high to be regarded as regular free market transactions. In the presence of such outliers in the estimation, the coefficients of EPC rating might be estimated with bias. Following Fuerst and McAllister (2011a), we also implement the robust regression approach using Huber and Turkey biweights to mitigate the potential error introduced by the outliers on coefficients estimates.

The outliers are identified using Cook's distance to capture the impact of dropping an observation based on its residual and its distance from the mean (called leverage). If an observation has Cook's distance large than 1, it will be dropped for regression. This iterative algorithm process stops when the maximum changes between the weights from one to the next is below tolerance. According to Verardi and Croux (2009), M-estimator from robust regression is adequately efficient, and can be found via

$$\sum_{i=1}^{N} \psi \frac{\left(Y - X\hat{\beta}\right)}{\sigma} X = 0 \tag{A.2}$$

where ψ is the first derivative of the objective function of $\rho(\varepsilon)$, which takes the form of a Huber function

$$\rho(\epsilon) = \begin{cases} 1/2\epsilon^2, & \text{if } \epsilon \leqslant k \\ k|\epsilon| - 1/2\epsilon^2, & \text{if } \epsilon > k. \end{cases} \tag{A.3}$$

And a Turkey Biweight function

$$\rho(\epsilon) = \begin{cases} 1 - \left(1 - (\epsilon/p)^2\right)^3, & \text{if } \epsilon \leqslant p \\ 1, & \text{if } \epsilon > p. \end{cases} \tag{A.4}$$

Parameter k and p determines the Gaussian efficiency of the estimator.

By applying the two forms of weighting functions, the most influential outliers are dropped, and then cases with large absolute residuals are down-weighted.

Both results from spatial autoregressive model and robust regression model are available from the authors upon request.

One could argue to allow precise control for location, distance from a dwelling to a public park, public facilities, bus stop, etc., should be included. We follow Jackson (1979) and Bracke (2015) and use the spatial polynomial function because traditional accessibility measures mentioned above are likely to provide disappointing results due to the interactions of complex forces in the determination the accessibility of any location (Jackson, 1979). To test the robustness of our models, we run all four models without geocodes related variables to see if omitting these variables would change the coefficients of EPCs and other key characteristics of the model. The results are shown in Table A.6. It suggests that if we allow random effects at postcodes level (as a control for neighbourhood as well as age), the coefficients EPC ratings and other housing characteristics do not change significantly.

To further test the sensitivity of EPC ratings among larger properties, we introduced a further dummy variable - large, to represent properties with four or more bedrooms. We then included EPC interacted with large properties in model 3 and 4. Coefficients of the key variables are presented in Table A.7.

Table A.6: Hedonic regression results of four forms in Eq. 2, 3, 4 for private residential leases rental data from ASPC during 2013Q3 to 2017Q3, without geocode.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Heating	0.0581***	0.0390***	0.0254	0.0300***
	(9.07)	(5.97)	(1.55)	(2.71)
Cloakrm	0.0765***	0.0625***	0.0645***	0.0697***
	(9.73)	(7.90)	(3.37)	(4.65)
Garage	0.0525***	0.0493***	0.0683***	0.0488***
	(8.06)	(7.58)	(4.26)	(4.03)
Garden	0.0107*	0.0140**	0.00571	0.0129
	(1.87)	(2.43)	(0.40)	(1.31)
Parking	0.0702***	0.0569***	0.0619***	0.0309***
	(14.93)	(11.80)	(5.57)	(3.89)
Newbuild	0.132***	0.0951***	0.0713*	0.0342
	(7.34)	(5.18)	(1.68)	(1.23)
TOM	0.00117***	0.00147***	0.000253	-0.00326
	(3.51)	(4.10)	(0.03)	(-0.63)
Furnish	0.153***	0.151***	0.188***	0.116***
	(31.23)	(30.98)	(16.99)	(14.83)
DetaSing	-0.0558***	-0.0403***	-0.0609**	-0.0505***
	(-5.34)	(-3.85)	(-2.55)	(-2.62)
DetaMulti	-0.0666***	-0.0547***	-0.0873***	-0.0294
	(-7.07)	(-5.80)	(-3.84)	(-1.61)
NondeSing	0.00848	0.00765	0.00774	-0.000646
	(0.75)	(0.68)	(0.30)	(-0.03)
FlatGround	0.0589***	0.0477***	0.101***	0.0395***
	(7.57)	(6.12)	(5.28)	(2.88)
FlatMid	0.0645***	0.0459***	0.0960***	0.0471***
	(8.39)	(5.91)	(4.95)	(3.40)
FlatTop	0.0679***	0.0604***	0.115***	0.0564***
	(7.39)	(6.59)	(5.06)	(3.59)
EPC_AB		0.107***	0.135***	0.0768***
		(10.24)	(5.37)	(4.64)
EPC_C		0.0492***	0.0599***	0.0531***
		(7.33)	(3.72)	(4.84)
EPC_D		0.0455***	0.0654***	0.0414***
		(7.09)	(4.31)	(4.03)
EPC_F		-0.0156	-0.0548**	-0.0379**
		(-1.63)	(-2.55)	(-2.50)
EPC_G		-0.0813***	-0.0867**	-0.0865***
		(-5.00)	(-2.38)	(-3.32)
α	8.366***	8.364***	8.267***	8.571***
	(57.58)	(56.29)	(25.50)	(25.52)
Year Quarter Vars	√	√	√	√
Coordinates Vars				
Multilevel 2-level				√
Interactive 2014Q3			√	√
Observations	9530	9461	9461	9451
R squared	66.66%	67.45%	68.44%	64.20%(1),63.81%(2)
Random Effect Parameters				
Level 1 property σ				0.1931***
Level 2 postcode σ				0.1101***
Likelihood ratio χ^2				4372.48***

t-statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
R^2 for 2-level regression is Snijders/Bosker R-squared.
Bryk/Raudenbush R-squared for 2-level regression is 67.31% for level 1, and 63.06% for level 2.

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Table A.7: Hedonic regression results of four forms in Eq. 3, 4 for private residential leases rental data from ASPC during 2013Q3 to 2017Q3, with *Large* variable included.

	Model 3	**Model 4**
Heating	0.0250	0.0300***
	(1.53)	(2.71)
Cloakrm	0.0647***	0.0682***
	(3.38)	(4.53)
Garage	0.0684***	0.0487***
	(4.27)	(4.02)
Garden	0.00584	0.0127
	(0.41)	(1.29)
Parking	0.0615***	0.0306***
	(5.53)	(3.86)
Newbuild	0.0710*	0.0343
	(1.67)	(1.24)
TOM	-0.0000287	-0.00322
	(-0.00)	(-0.63)
Furnish	0.189***	0.116***
	(17.01)	(14.82)
DetaSing	-0.0608**	-0.0513***
	(-2.54)	(-2.65)
DetaMulti	-0.0881***	-0.0317*
	(-3.87)	(-1.73)
NondeSing	0.00712	-0.00239
	(0.28)	(-0.12)
FlatGround	0.100***	0.0382***
	(5.24)	(2.78)
FlatMid	0.0951***	0.0462***
	(4.90)	(3.34)
FlatTop	0.114***	0.0551***
	(5.01)	(3.51)
EPC_AB	0.139***	0.0756***
	(5.49)	(4.53)
EPC_C	0.0621***	0.0533***
	(3.81)	(4.81)
EPC_D	0.0688***	0.0445***
	(4.48)	(4.27)
EPC_F	-0.0486**	-0.0357**
	(-2.22)	(-2.32)
EPC_G	-0.0831**	-0.0821***
	(-2.25)	(-3.15)
Large×EPC_B	-0.0396	0.0335
	(-1.20)	(1.07)
Large×EPC_C	-0.0161	-0.000899
	(-0.84)	(-0.05)
Large×EPC_D	-0.0264	-0.0326*
	(-1.38)	(-1.78)
Large×EPC_F	-0.0432	-0.0234
	(-1.64)	(-0.89)
Large×EPC_G	-0.0297	-0.0874
	(-0.55)	(-1.51)
α	8.290***	8.593***
	(25.55)	(25.55)
Year Quarter Vars	√	√
Coordinates Vars	√	√
Multilevel 2-level		√
Interactive 2014Q3	√	√
Observations	9461	9451
R squared	80.77%	81.08%(1),82.78%(2)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Highlights

- Private tenants pay a premium for properties with higher energy performance.
- The willingness to pay is considerable.
- Such willingness to pay is significantly reduced during economic downturn.
- The private housing sector may need public strategy to improve energy performance.

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