The effect of weather on the willingness to pay for energy-efficiency: Evidence from the UK housing market

Rodolfo Sejas-Portillo*, Mirko Moro and Till Stowasser

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Abstract

We study the effects of weather conditions on the economic valuation of energy-efficiency (EE) in the UK housing market. Individuals make valuations based on the total utility that they expect to derive from a product and its features. In the UK housing market, utility is almost exclusively realised in the future as buyers make a priced offer over a month before the sale transaction is complete and they are able to either move in or rent the property. While the value of EE features (e.g. insulation) depends directly on the expected weather over the ownership time frame (e.g. for maintaining heat during cold periods), due to its notorious unpredictability, present weather conditions provide little to no additional information about future weather conditions (beyond common knowledge such as seasonal temperature differences). Nonetheless, using transaction-level data of over 5 million residential property sales in England and Wales, we find that weather conditions during the month the buying decision is made can disproportionately influence the EE valuation of properties: During rough weather (i.e. cold and rainy) the EE rating of a property has a stronger influence on its sale price than during favourable weather (i.e. warm and dry). We show that these results are unlikely to be driven by energy-cost optimisation behaviour. We model and discuss potential mechanisms for these findings within an intertemporal decision framework (to investigate projection bias and over-inference) and within a limited attention framework (to investigate salience). We provide policy considerations for educational interventions.

*Corresponding author: Rodolfo Sejas-Portillo, Economics Division, Stirling Management School, University of Stirling, FK9 4LA, Scotland, UK. Email: rodolfo.sejasportillo@stir.ac.uk.

1 Introduction

Purchasing decisions rely on the adequate economic valuation of a product and its features. Individuals make these valuations based on the utility that they expect to derive from consuming or holding ownership of a product. In asset and investment markets utility is almost exclusively realised in the future. For example, when deciding to purchase a house, the expected utility will include the forthcoming benefits of living in the property and the expected price appreciation over time. Assessing future utility is then an intertemporal problem where individuals, at the time of the purchase decision, need to estimate all future benefits and costs. While neoclassical economic models typically assume that individuals are able to make these intertemporal estimations accurately (Rabin 2002*b*), current research suggests that they are susceptible to making systematic mistakes (see Ericson & Laibson 2019 and DellaVigna 2009 for reviews of the literature). For instance, individuals may incorrectly project their current preferences into the future (projection bias – see Loewenstein et al. 2003), be inattentive to information relevant to future utility (limited attention bias – see Gabaix 2019) or make overinferences about the future state of the world from a small set of recent past observations (overinference bias – e.g. Rabin 2002*a* and Benartzi 2001). Recent research suggests that external factors, such as the weather, can aggravate these biases and thus have an important influence on the efficiency of intertemporal economic valuations and their corresponding purchasing decisions (e.g. Busse et al. 2015, Conlin et al. 2007).

This paper presents evidence that weather conditions can disproportionately influence the economic valuation (price premia) of energy-efficiency (EE) in the UK housing market. In the UK, sellers must provide an energy performance certificate (EPC) for the property to potential buyers at the first point of contact (e.g. as part of advertisement materials or during an arranged viewing), long before a price is agreed upon. One of the main components of the EPC is the EE rating (also referred to as SAP rating), an standardised numerical score ranging from 1 (for the least efficient properties) to 100 (for the most efficient). We find that if the weather was rough (i.e. cold and/or rainy) during the month the buying decision was made, the EE rating of a property has a stronger influence on the final sale price than if the weather was favourable (i.e. warm and/or dry).

Policies that rely on economic incentives and market mechanisms are normally designed assuming accurate and consistent product valuations across time. If the influence on market valuations of external factors that policy makers cannot control – such as the weather – are ignored, the impact of policies will be difficult to predict and manage (e.g. as part of a cost-benefit analysis). For instance, as discussed in Sejas-Portillo et al. (2020), price premiums resulting from EE ratings have an important effect on the decision by sellers to invest in EE improvements before marketing their property.

Using data on over 5 millions sale transactions from England and Wales, we find that on average, an increase of 10 EE rating points leads to a sale price increase of 1.687 percentage points (£4,461 based on average sale prices) if the average air temperature was $5C^{\circ}$ during the month the buying decision was made. However, the same 10 points increase in the EE rating would lead to an increase in price of only 0.385 percentage points (£1,018) if the average temperature was $20C^{\circ}$.[1]

[1] It is important to note that the UK housing market is seasonal, with most sales occurring during summer, nonetheless we rule out in our analysis that the weather effects we document are driven by market seasonal differences.

We find a similar effect for rainfall: If total rainfall was $1cm$ for the month the buying decision was made, a 10 EE rating-points increase leads, on average, to a 0.552 percentage-point increase (£1,459.71) in the sale price. Yet, if the total monthly rainfall was $15cm$, a 10 EE rating-points increase leads to a much higher 1.914 percentage-point increase in prices (£5,061.68). Moreover, we show that the relationship between air temperature and EE valuation is kinked, with the effects considerably more sensitive for very cold temperatures (less than $6.5C^{\circ}$) and very warm temperatures (more than $17C^{\circ}$). Intuitively, the kinked effect is expected since people are more sensitive to distinctively low and distinctively high temperatures. We discuss the importance of the kinked effects given the increasing frequency of extreme weather events (attributed to climate change) and the differences in temperatures across regions in England and Wales.

We show that the effects we identify are unlikely to be due to rational optimisation of running fuel costs. We propose that the effects are rather driven by psychological biases. We model and discuss projection bias (Loewenstein et al. 2003), overinference bias (Rabin 2002*a*) and salience (Gabaix 2019) as the most likely potential explanations. Our transactional data does not allow us to differentiate between these biases, and thus we do not argue for any as the main driver.[2] Our results are consistent with the notion that individuals understand qualitatively the benefits of EE, but underestimate the magnitude of the utility derived due to the biases described above (Loewenstein et al. 2003). We present evidence that some individuals appear to behave (bounded) rationally and take corrective action, in the form of future EE investments, once they realise their

[2]It is worth noting that emotion tagging (Dolan 2002, Laudenbach et al. 2019) can also play a role in the biased utility estimations. For example, individuals who experienced a particularly cold winter can emotionally value EE higher, aggravating the biases we document.

mistaken utility predictions.

Our paper directly contributes to the literature investigating the effects of external factors on intertemporal utility estimations during market transactions. Closely related to our paper, Conlin et al. (2007) find that weather conditions over-influence the decisions to purchase cold-weather apparel, and they provide evidence that projection bias is the likely mechanism behind these decisions. Similarly, Busse et al. (2015) show that weather conditions, at the time of purchase, influence the decision of individuals to buy convertibles and four-wheel-drive cars. They too propose projection bias as one of the mechanisms behind the decisions, but put forward the notion that salience can play a role as well. Our results show that weather conditions can also influence decisions in the housing market,[3] where corrective action can be more expensive and difficult once individuals realise their mistakes (e.g. having to replace all windows with triple glazing). We further contribute to this literature by providing an identification strategy for the effects of weather conditions on product-feature valuations (i.e. how much people are willing to pay for certain features), as opposed to only the final decision to purchase. In addition to projection bias and salience, we suggest overinference as another mechanism behind these effects and provide an intertemporal valuation model that can explain our results. Our paper adds to the literature on housing EE, Comerford et al. (2020) and Sejas-Portillo et al. (2020) provide policy recommendations for increasing retrofitting by improving the design of the EE labels used for properties in the UK (and across the European Union). Our results suggest that implementing labelling strategies that include cues and reminders about the different weather

[3] A working paper version of Busse et al. (2015) also looks at the housing market, showing that weather conditions have an effect on the decisions to purchase houses with swimming pools.

conditions can further improve their effectiveness.

Our paper also contributes to the literature on the empirical estimation of kinked effects using a regression kink design (RKD – Nielsen et al. 2010, Card et al. 2015). We derive the additional assumptions required for the identification of kinked effects of interacted terms and present a non-parametric estimator. We show the applicability of this estimator by documenting the kinked effects of air temperature on EE valuation as explained above.

The remainder of the paper is organised as follows. Section 2 describes the transaction-level data used for our analysis and the structure of the housing market in the UK. Section 3 discusses our empirical strategy and presents the results of our average-effects estimations. Section 4 details our identification and estimation strategies for interacted effects in a RKD and presents the results obtained for the kinked effects of air temperature on EE valuation. Section 5 discusses potential explanations for our results. Finally, Section 6 concludes.

2 Data

We analyse transaction-level data of over 5 million residential property sales in England and Wales from June 2012 to January 2020. We use the dataset from Sejas-Portillo et al. (2020) which merges information from: a) Her Majesty's Land Registry (HMLR) Price Paid Data; b) The Department for Communities and Local Government (DCLG) Energy Performance of Buildings Data: England and Wales; and c) Rural Urban Classification official statistics.[4] Each transaction contains sale price, sale date, property characteristics, geographic location and EE

[4] For a detailed explanation of the different datasets and the process to aggregate them see the Data section of Sejas-Portillo et al. (2020).

information. The EE information comes from a mandatory energy performance certificate (EPC) that must be commissioned before marketing the property for sale. The EPC includes a numerical EE rating score for the property (referred to as SAP rating) ranging from 1 (for the least efficient) to 100 (for the most efficient). The EE rating is an energy cost rating based on engineering calculations and standardised across properties of different types and sizes (for a detailed explanation see Sejas-Portillo et al. 2020). We exclude transactions prior to June 2012 as the legislation in place could be interpreted as requiring sellers to show the EPC to buyers before the sale was completed (i.e. before contracts were signed), but not necessarily before a price was agreed. Policy amendments came into effect in 2012 clarifying the requirement to include the EE rating graph in all marketing materials (printed and online), effectively meaning that buyers would have seen the rating before agreeing on a price.[5] We also exclude new and repurposed buildings from our analysis because, as explained in Sejas-Portillo et al. (2020), these usually follow a different selling process where an EPC may not be available when a price is agreed and therefore the EE rating in the EPC may not reflect the EE valuation of market participants.[6]

We match each sale transaction to monthly air temperature and rainfall data for the geographic region where the property is located (9 regions in England plus Wales). Air temperature is measured in degrees Celsius C° as the daily mean air temperature averaged over the calendar month. Rainfall is measured as the total cumulative precipitation during the calendar month in cm. The weather data

[5] Sejas-Portillo et al. (2020) provides an in-depth explanation of EPC policies and legislation in the UK.

[6] A small amount of transactions where the number of rooms is missing (12,069 of 5,337,903 transactions – 0.23%) was also excluded since we use this variable as a control for our analysis.

was obtained from the HadUK-Grid dataset published by the Met Office (the UK national meteorological office). Regional weather values are produced by interpolating weather information from land surface climate observation stations and averaging them across the geographic boundaries of the region (see Met Office 2019 for details on weather data collection, interpolation and geographic composition).

Tables 1 and 2 show summary statistics for key variables used in our analysis. A slight seasonality of the market is evident in our data, with 28.5% of sale transactions registered in the third quarter (summer sales) compared to 21.5% during the first quarter (winter sales). The majority of the transactions in our dataset (39.1%) are from the south of England (London, South East and South West), where the weather is relatively warm on average, and a smaller proportion (26.2%) are from the north of England (North East, North West and Yorkshire and The Humber) which, conversely, has colder weather on average. The remaining proportion (34.7%) are from regions in central England (East Midlands and West Midlands) and Wales. The differences in the sale frequencies of each region suggest different market dynamics and the importance of controlling for geographic area effects in our analysis. We also observe marked differences in the frequencies of built types (31.8% are for terraced properties compared to 15.2% for flats) and property construction ages (with most properties built before 1976 – 68.9%). Even though the EPC energy audit takes into account built characteristics and produces a standardised EE rating, our analysis controls for them as EE features and sale prices can differ considerably. For example, while detached houses generally sell for higher prices, a flat that has other flats above and below will achieve a high EE rating without the need for roof or floor insulation (a detached property may require all round insulation to achieve a similar EE rating). The tenure of a property represents the ownership of the land and the building: Freehold grants permanent ownership to both, whereas leasehold represents ownership of the building but a long term lease for the ground (99+ years).[7] Freehold properties sell for higher prices on average. The majority of transactions we observe are for freehold properties (79.9%) and most leasehold transactions are for flats (74%). The frequency distribution of sales across the EE rating scale is approximately normal (see Sejas-Portillo et al. 2020 for a frequency histogram), the average EE rating is 60 and the large majority of properties have a rating band of C or D (72.2%). The average sale price in our dataset is 264,398, the average total floor area is $94m^2$ and the average number of rooms is 5.[8] Finally, the average monthly mean air temperature is $10.78C^{\circ}$ and the average monthly total rainfall is $7.53cm$.

Table 1: Summary statistics for continuous variables

	Mean	*SD*	*Min*	*Max*
Price Paid (£)	264,397.77	288,719.04	1,000.00	46,131,500.00
Total Floor Area (m^2)	93.83	46.88	30.00	8,824.00
Price per Square Meter (£/m^2)	2,813.57	1,930.37	3.92	220,920.64
Number of Rooms	4.67	1.66	1.00	99.00
Energy Efficiency (SAP Rating)	60.19	12.66	1.00	100.00
Monthly Mean Air Temperature (C°)	10.78	4.59	1.34	21.25
Monthly Total Rainfall (cm)	7.53	4.34	0.06	33.69
Observations	5,325,834			

Notes: This table presents summary statistics for key continuous variables. SD stands for Standard Deviation.

[7] Freeholders usually pay rent to the owner of the ground.

[8] As explained in Sejas-Portillo et al. 2020, the dataset excludes properties with a total floor area of less than $30m^2$ and sale prices of less than 1,000 as these are not realistic.

Table 2: Summary statistics for categorical variables

Variable	*Freq.*	%	Variable	*Freq.*	%
Property Type			Sale Quarter		
Detached	1,248,699	23.4	Quarter 1	1,147,474	21.5
Flat	807,404	15.2	Quarter 2	1,187,645	22.3
Semi-detached	1,574,030	29.6	Quarter 3	1,516,799	28.5
Terraced	1,695,701	31.8	Quarter 4	1,473,916	27.7
Tenure			Sale Year		
Freehold	4,253,899	79.9	2012	324,932	6.1
Leasehold	1,071,935	20.1	2013	622,112	11.7
Region			2014	743,631	14.0
North East	225,279	4.2	2015	740,225	13.9
North West	669,198	12.6	2016	730,607	13.7
Yorkshire and The Humber	502,031	9.4	2017	718,160	13.5
East Midlands	468,090	8.8	2018	701,812	13.2
West Midlands	501,653	9.4	2019	693,967	13.0
East	614,137	11.5	2020	50,388	0.9
London	588,932	11.1	Construction Age Band		
South East	911,472	17.1	Before 1900	586,439	11.0
South West	577,969	10.9	1900-1929	785,376	14.7
Wales	267,073	5.0	1930-1949	783,932	14.7
Area Density			1950-1966	866,647	16.3
Rural	989,372	18.6	1967-1975	651,996	12.2
Urban	4,336,462	81.4	1976-1982	311,628	5.9
EE Rating Band			1983-1990	413,286	7.8
A	1,020	0.0	1991-1995	209,075	3.9
B	100,608	1.9	1996-2002	317,444	6.0
C	1,268,464	23.8	2003-2006	256,420	4.8
D	2,576,365	48.4	2007 Onwards	112,586	2.1
E	1,061,985	19.9	Unknown	31,005	0.6
F	253,164	4.8			
G	64,228	1.2			
Observations		5,325,834			

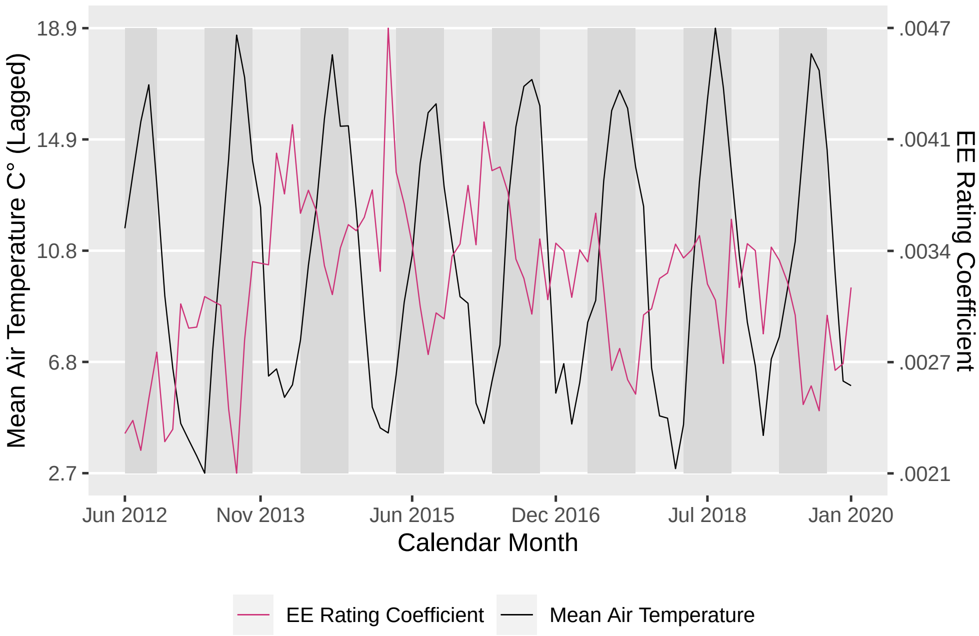
Notes: This table presents the frequencies and proportions (%) for key categorical variables.

Figure 1 gives a sense of the relationship between EE ratings and sale prices across each calendar month, and how it compares to the variation in monthly mean air temperature. For this, we plot (in red) the coefficients from regressions of the EE rating on price per meter (log) for each calendar month,[9] and (in black) the monthly mean air temperature, lagged by one month to account for the time between the date a sale is agreed on (i.e. an offer accepted) and the date it is

[9] We run the regressions separately for each month. Using R^2 instead of the coefficient shows a similar trend.

completed.[10] A striking pattern is clearly visible: As temperatures rise the relationship between the EE rating and the sale price becomes weaker, and conversely as temperatures drop the relationship becomes stronger. Sections 3 and 4 provide formal estimations of these effects.

Figure 1: Air temperature - EE rating coefficient on sale price



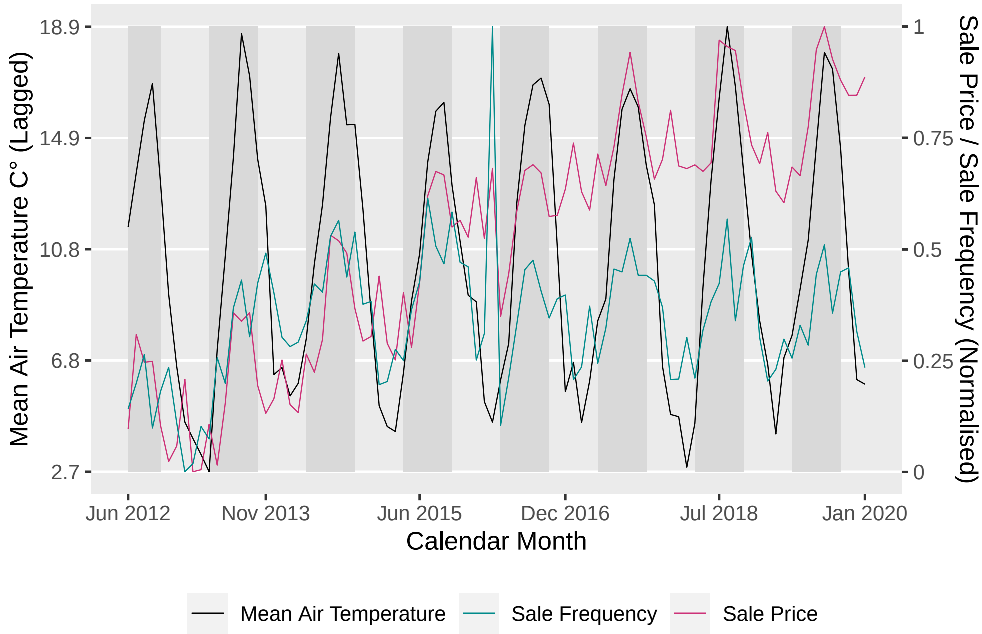
Notes: This figure plots the coefficients from a regression of EE rating on price per meter (log) for each calendar month and the average monthly mean air temperature for the UK. The mean air temperature is lagged by one month to account for the time between the date a sale is agreed upon and the date it is completed.
N=5,325,834.

An important concern for our analysis is the seasonality of the housing market in the UK. The activity in the housing market increases during summer and decreases during winter. As a result the sale frequencies and prices are higher during

[10] A detailed discussion of the importance of the lag for our analysis is included in Section 3.

the summer months. Figure 2 illustrates this seasonality by showing monthly averages for the number of transactions and sale prices, and as before it also shows the monthly mean air temperature lagged by one month. The correlation between market activity and air temperature is visible, and thus, it is important for our formal analysis in Sections 3 and 4 to control for local market conditions. We show in our results that market conditions do not influence the effect of EE ratings on sale prices and that they are mostly orthogonal to EE valuation.

Figure 2: Air temperature - Market conditions



Notes: This figure plots monthly sale frequencies, monthly average sale prices and the average monthly mean air temperature for the UK. The mean air temperature is lagged by one month to account for the time between the date a sale is agreed upon and the date it is completed.
N=5,325,834.

3 Estimation of weather effects on EE valuation

Our identification strategy involves testing if weather conditions, close to the time a buying offer is made, influence the EE valuation of a property. The housing market in the UK follows a double auction structure where buyers make offers that sellers can then accept or reject. As we observe final sale transactions, the recorded price is the latest offer from a buyer that was accepted by a seller, and thus it reflects the final market valuation of a property. We study EE valuation by estimating the effect that the EE rating of a property has on its final sale price. The relationship between the EE rating and the final sale price captures the importance that buyers place on EE, in other words their economic valuation for EE benefits (e.g. thermal comfort, lighting needs). It is important to note that the EE rating, which – as mentioned above – is standardised and ranges from 1 to 100, cannot be precisely predicted before the EPC energy audit is performed. Thus the distribution of properties of different characteristics (e.g. size, type), locations and EE features (e.g. insulation, triple glazing, boiler type) is effectively random at each EE rating score, allowing us to study EE valuation as such as opposed to specific property features.

In practice, the precise time when the buying decision was made is unobservable: It can take several weeks before an offer is accepted, contracts are signed and the ownership transferred. The sale date in our dataset is the date when the sale was completed, as stated in the transfer of deed (HMLR 2016). Furthermore, the EE valuation is likely to be influenced not only by the weather conditions on the day the decision was made but also on the days or weeks leading up to it. Thus, we use the weather conditions of the month before the sale was completed

$E[W|t-1]$ in our estimations. We use the previous calendar month to simplify the interpretability of our results from a policy perspective, but our estimates are essentially the same if we use a lagged 30-day rolling average.[11]

We use the weather conditions within the region where the property is located for our analysis. UK wide weather data is too coarse a measure and would introduce higher measurement error. Using regional data follows a more micro approach and offers better, more granular variation.[12] While we cannot observe the previous living or working locations of buyers in our dataset, people in the UK exhibit low regional mobility (for a detailed discussion and estimates see Langella & Manning 2019 and Coulter & Scott 2015).

3.1 Pooled cross-sectional estimation

We start with a pooled cross-sectional regression analysis (i.e. we treat all sale transactions as independent[13]) of the relationship between the EE rating, the sale price and weather conditions using the following specification:

$$P_i = \alpha + \beta EE_i + \delta \boldsymbol{W_{r,t-1}} + \theta EE_i * \boldsymbol{W_{r,t-1}} + \gamma \boldsymbol{Z_i} + \varepsilon_i \tag{1}$$

Where P_i represents the price per meter (log) of property i and EE_i represents

[11]We show in Appendix B that our results are robust to alternative lags for the weather conditions. The estimates using a lagged 30-day rolling average are available from the authors upon request.

[12]We repeat our analysis using the weather conditions for all of the UK and show in Appendix B that our results hold.

[13]We show in Appendix B that our results for EE interacted with weather conditions remain mostly unchanged if we exclude properties that were sold more than once.

its EE rating. $W_{r,t-1}$ is a vector of weather conditions, namely monthly mean air temperature and monthly total rainfall, for region r (the region where property i is located) and month $t-1$, as explained above we lag the month to account for the time it takes from the moment an offer is made to the date the sale is completed. Z_i is a vector of control covariates for property characteristics (property type, tenure, property age and number of rooms), location (UK local authority district and urban/rural classification) and date (sale year and month). The interaction term $EE_i * W_{r,t-1}$ captures the additional effect that the EE rating has on price under different weather conditions.The coefficients of interest are β, which captures the effect of EE on price, and θ, that captures the effect of the interaction term. We interpret the results as the first derivative of equation (2) with respect to EE:

(1a) $$\frac{\partial P}{\partial EE} = \beta + \theta \boldsymbol{W_{r,t-1}}$$

As previously explained, the housing market is seasonal with more sales occurring during the summer months. Thus, it is important to rule out that our results are driven by spurious variation in local market conditions (i.e. the 'hotness' of the market) which may be correlated with the weather (e.g. people going on fewer viewings during rainy days). Specification (1) partially already controls for local market characteristics by including dummy indicators for the sale month-year and the local authority district (LAD) geographic level. LADs are administrative units in England and Wales with responsibilities including local planning, housing and building (ONS 2020), and thus they provide a good delimitation for static local housing-market conditions (there are 339 LADs in our dataset). To further control for dynamic conditions of the housing market within each LAD, we extend our specification to include two measures of local market dynamics: The number of sales per month in the LAD (demeaned), and the average sale price per month in the LAD (de-trended, normalised and demeaned). Specific calculations of these market measures are included in Appendix A. The specification that controls for time-varying local market conditions is:

$$(2)\ \ P_i = \alpha + \beta EE_i + \delta \boldsymbol{W_{r,t-1}} + \theta EE_i * \boldsymbol{W_{r,t-1}} + \mu \boldsymbol{M_{a,t}} + \tau EE_i * \boldsymbol{M_{a,t}} + \gamma \boldsymbol{Z_i} + \varepsilon_i$$

Where M_a is a vector of the market conditions described above (local sale frequency and price measures) for local area a (the LAD where property i is located). We also interact the EE rating with the vector of market conditions to show that the additional effect of weather on EE valuation is not the result of varying market conditions.

Table 3 presents the estimates for Specifications (1) and (2). We centre the EE rating, weather variables and market conditions at their means to show that the coefficient for EE remains stable when adding the interactions terms.[14] Column (1) shows the coefficients for a regression on price per meter (log) of the EE rating and the vector of covariates Z_i, Column (2) adds the vector of weather conditions $W_{r,t-1}$.[15] Column (3) shows our estimations using Specification (1) and

[14]Centring these variables at their means does not change the estimation of the coefficients for the interaction terms.

[15]Columns (1) and (2) are included to show the stability of our results.

Column (4) using Specification (2) which includes the vector $M_{a,t}$ of local market conditions. The coefficient for EE is remarkably consistent across all specifications, and indicates that for a 1 point increase in the EE rating score the price per meter of a property increases by 0.119 percentage points on average, holding air temperature and rainfall constant at their averages. It is worth noting that the coefficient for air temperature, although positive, loses statistical significance when controlling for market conditions, providing evidence that our market controls adequately capture the seasonality of local markets and that the effect of air temperature on property prices is through its relationship with the EE features (i.e. our interaction terms).

The main coefficients we are interested in are the interactions between the EE rating and weather conditions (air temperature and rainfall). These are statistically significant at the 0.1% level and, importantly, do not change much after controlling for market conditions. We interpret the results using Equation (1a), the first derivative of our specifications with respect to the EE rating. The coefficient θ of the interaction between the EE rating and air temperature indicates that a $1C^{\circ}$ increase in mean air temperature (on the month prior to the sale completion) reduces the effect of the EE rating on the price per meter of a property by 0.009 percentage points on average. Similarly, for rainfall the coefficient θ indicates that a $1cm$ increase in rainfall increases the effect of the EE rating on the price per meter of a property by 0.01 percentage points on average. The signs of both coefficients are as expected. These results confirm our intuition, that during cold temperatures individuals are more price sensitive towards EE (e.g. heating for comfort) and to energy costs, which translate to a higher valuation for the EE rating. As temperature raises they become less sensitive to these features and energy costs, and thus the EE rating has a less prominent role in the sale price of properties. Similarly, during rainy periods people seem to value EE more and prices are more sensitive to the EE rating of the property. These results are not aligned with fully rational behaviour, we present a more in-depth discussion of their implications in Section 5.

These effects are also economically significant, and as such have the potential to influence seller EE investment decisions. For instance, using marginal effects at the means (MEM) estimations with Specification (2), we find that a 10 EE rating points increase leads to a sale price increase of 1.687 percentage-point (£4,461 based on the average sale price) if the air temperature on the previous month was $5C^{\circ}$. However, the same 10 EE rating points increase leads to only 0.385 percentage-point increase in price (£1,018) if the air temperature during the previous month was $20C^{\circ}$. Similarly, a 10 EE rating points increase when the total rainfall for the previous month was $1cm$ increases the sale price by 0.552 percentage points on average (£1,459.71), but the same increase in the EE rating leads to a much bigger increase of 1.914 percentage points (£5,061.68) if the total rainfall was $15cm$.

Table 3: Pooled cross-sectional results

	(1)	(2)	(3)	(4)
EE Rating	0.119***	0.119***	0.118***	0.119***
	(0.009)	(0.009)	(0.009)	(0.009)
Temperature		0.212**	0.248***	0.094
		(0.064)	(0.066)	(0.082)
Rainfall		−0.005	−0.002	−0.004
		(0.014)	(0.015)	(0.014)
EE Rating*Temperature			−0.008***	−0.009***
			(0.001)	(0.001)
EE Rating*Rainfall			0.010***	0.010***
			(0.002)	(0.002)
Property Characteristics	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Local Market FE				Yes
EE Rating*Local Market FE				Yes
R-squared	0.721	0.721	0.721	0.721
Observations	5,325,834	5,325,834	5,325,834	5,325,834

Notes: Standard errors in parentheses. * significant at 5%; ** significant at 1% *** significant at 0.1%. Coefficients and standard errors have been multiplied by 100 to interpret them as percentage point increases. Standard errors clustered at the LAD level. The EE Rating ranges from 1 to 100. Temperature is measured in C° and Rainfall in *cm*. Property Characteristics FE include property type, tenure and number of rooms. Location FE include LAD and urban/rural classification. Date FE include sale year and month. Local Market FE add number of sales per month in the LAD (normalised and demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned). Column (1) presents the results of a regression of EE rating and baseline covariates on price per meter (log). Column (2) adds weather conditions on the month prior to the sale. Column (3) shows the results of Specification (1). Column (4) shows the results of Specification (2).

3.2 Property fixed-effects estimation

We also perform our analysis using property fixed-effects specifications, as there may be some unobservable property characteristics that systematically affect the selling price during certain seasons. For example, properties that have large gardens can be seen as more desirable during summer and command higher prices, but having a larger garden is not correlated with EE and should not influence EE valuation. Using a sub-sample of properties for which we observe more than one sale (1,329,057 transactions in total), we estimate property-level fixed-effects regressions with the following specifications:

$$(3) \qquad \tilde{P}_{i,t} = \beta \tilde{EE}_{i,t} + \delta \tilde{\boldsymbol{W}}_{\boldsymbol{r,t-1}} + \theta \tilde{EE}_{i,t} * \tilde{\boldsymbol{W}}_{\boldsymbol{r,t-1}} + \tilde{\boldsymbol{Z}}_{\boldsymbol{i}}\gamma + \nu_{i,t}$$

$$(4) \quad \tilde{P}_{i,t} = \beta \tilde{EE}_{i,t} + \delta \tilde{\boldsymbol{W}}_{\boldsymbol{r,t-1}} + \theta \tilde{EE}_{i,t} * \tilde{\boldsymbol{W}}_{\boldsymbol{r,t-1}} + \mu \tilde{\boldsymbol{M}}_{\boldsymbol{a,t}} + \tau \tilde{EE}_{i,t} * \tilde{\boldsymbol{M}}_{\boldsymbol{a,t}} + \tilde{\boldsymbol{Z}}_{\boldsymbol{i}}\gamma + \nu_{i,t}$$

Where the tilde ($\tilde{\_}$) variables are the property-level demeaned versions of the ones introduced in Specifications (1) and (2). As before, the coefficients of interest are β and θ. Importantly, the coefficient β for EE in this specification captures how much the variability in the EE rating *score* affects the variability in price. The majority of properties that were sold more than once increased their EE rating between sales (55.65% of the transactions).[16] An improvement in EE features will normally indicate that other improvements were also made to the property. For instance, after installing new insulation, walls will typically be re-painted and flooring redone, which will increase the final sale price of the property irrespective of the EE gains. Similarly, sellers who are investing in EE improvements may be aiming for higher sale returns and thus also invest in other improvements such as

[16] In 55.65% of the sale transactions the current EE rating was higher than the previous one for the same property, 41.61% was the same and 2.74% was lower. Lower EE ratings can occur for example when extensions are added to a house or when the boiler is changed.

exterior redecoration, which again will not impact EE. The EE-rating coefficient β captures all of these differences and is thus expected to be larger than the one in our cross-sectional specification. Conversely, the θ coefficients for the interactions between EE rating and weather conditions (air temperature and rainfall) are expected to be smaller since, according to our argument, these capture the effect of weather conditions on EE valuation, which, as explained above, is only a portion of the total effect of the EE rating score on price. This provides further evidence that weather conditions influence sale prices mainly through the features that individuals associate with EE.

Table 4 presents the results from our property fixed-effects analysis. Column (1) shows the coefficients from a regression on price per meter (log) of the EE rating and the vector of control covariates $\tilde{Z}_i$, Column (2) adds the vector of weather conditions $\tilde{W}_{r,t-1}$, Column (3) shows the estimation using Specification (3), and Column (4) using Specification (4). Similar to our cross-sectional analysis, the coefficients are remarkably consistent across all specifications and the signs and statistical significance of our estimations confirm the direction of the effect of weather conditions on EE valuation. As discussed above, the coefficient β for the EE rating is higher, at 0.459, as it captures other improvements made to the property in addition to EE features. The interaction terms θ for EE rating with air temperature (-0.002) and rainfall (-0.001) are nominally smaller than in our cross-sectional analysis.

Table 4: Property fixed-effects results

	(1)	(2)	(3)	(4)
EE Rating	0.461***	0.461***	0.460***	0.459***
	(0.017)	(0.017)	(0.016)	(0.016)
Temperature		0.470***	0.485***	0.344***
		(0.087)	(0.087)	(0.085)
Rainfall		0.002	0.003	0.003
		(0.018)	(0.018)	(0.018)
EE Rating*Temperature			−0.003***	−0.002***
			(0.000)	(0.000)
EE Rating*Rainfall			0.003***	0.003***
			(0.001)	(0.001)
Property Characteristics	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Local Market FE				Yes
EE Rating*Local Market FE				Yes
R-squared	0.505	0.505	0.505	0.506
Observations	1,329,057	1,329,057	1,329,057	1,329,057

Notes: Standard errors in parentheses. * significant at 5%; ** significant at 1% *** significant at 0.1%. Coefficients and standard errors have been multiplied by 100 to interpret them as percentage point increases. Standard errors clustered at the LAD level. The EE Rating ranges from 1 to 100. Temperature is measured in $C°$ and Rainfall in *cm*. Property Characteristics FE include property type, tenure and number of rooms. Location FE include LAD and urban/rural classification. Date FE include sale year and month. Local Market FE add number of sales per month in the LAD (normalised and demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned). Column (1) presents the results of a property fixed-effects regression of EE rating and baseline covariates on price per meter (log). Column (2) adds weather conditions on the month prior to the sale. Column (3) shows the results of Specification (3). Column (4) shows the results of Specification (4).

4 Heterogeneity of weather effects

In this section we study whether the uncovered effects are linear or if the effect of severe weather conditions differ from those of mild weather conditions. Figure 3 shows our estimated effect of air temperature on EE valuation (the coefficient for

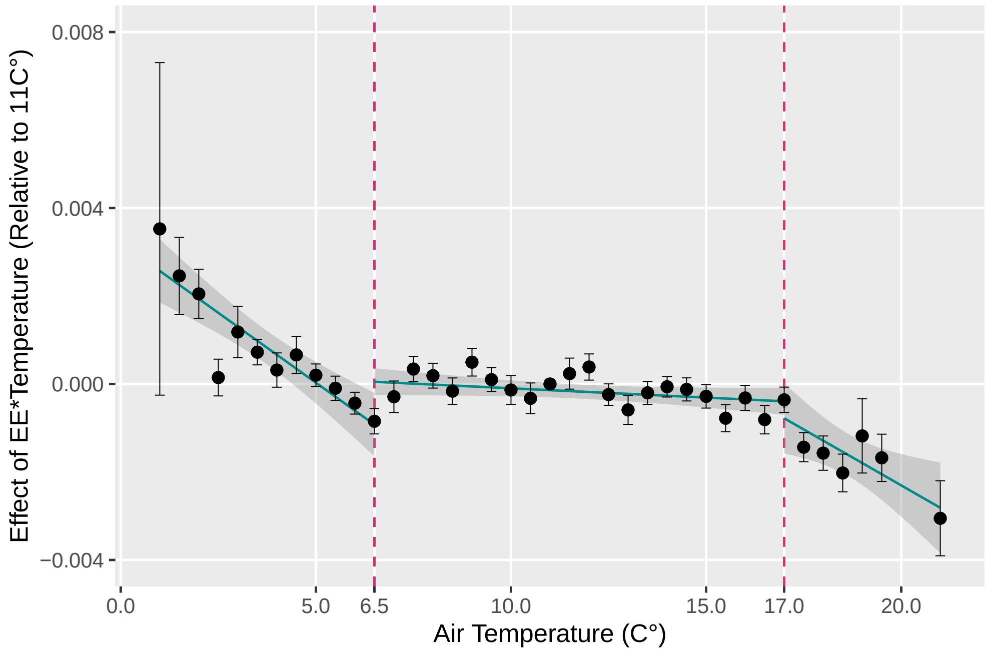
$EE_i * W_{r,t-1}$ from Specification 2) across the entire air temperature range. We create bins for sale transactions at $0.5C^{\circ}$ intervals and plot the coefficients and their confidence intervals at the 95% level. The average monthly air temperature in our dataset ($11C^{\circ}$) is used as the hold-out bin category.[17] We can see that the effect on price decreases sharply from $1C^{\circ}$ to around $6.5C^{\circ}$, thereafter the relationship stays mostly flat up to around $17C^{\circ}$ where is starts decreasing sharply again. We plot linear fits to highlight the kinked functional form. The different slopes show that if the mean air temperature is below $6.5C^{\circ}$, EE has a larger effect on sale prices (i.e. individuals value EE more). The magnitude of this effect increases as the temperature gets lower. Similarly, if the mean air temperature is above $17C^{\circ}$, EE has a increasingly smaller effect on sale prices.

We perform the same analysis for rainfall but do not find non-linear effects. Figure 4 presents the estimated effect of rainfall on EE valuation, with $1cm$ bins relative to $7cm$ (the average rainfall in our dataset). As before we use the coefficient and 95% confidence intervals for the interaction term EE*Rainfall from Specification (2). The effect appears to follow a linear trend, the more it rains the more individuals value EE.

Intuitively, these functional forms are to be expected, individuals are sensitive to very cold temperatures (the kink at $6.5C^{\circ}$) and to very warm temperatures (the kink at $17C^{\circ}$), but they are only progressively sensitive to rainfall (e.g. under the perception that once it starts raining it only gets worse).

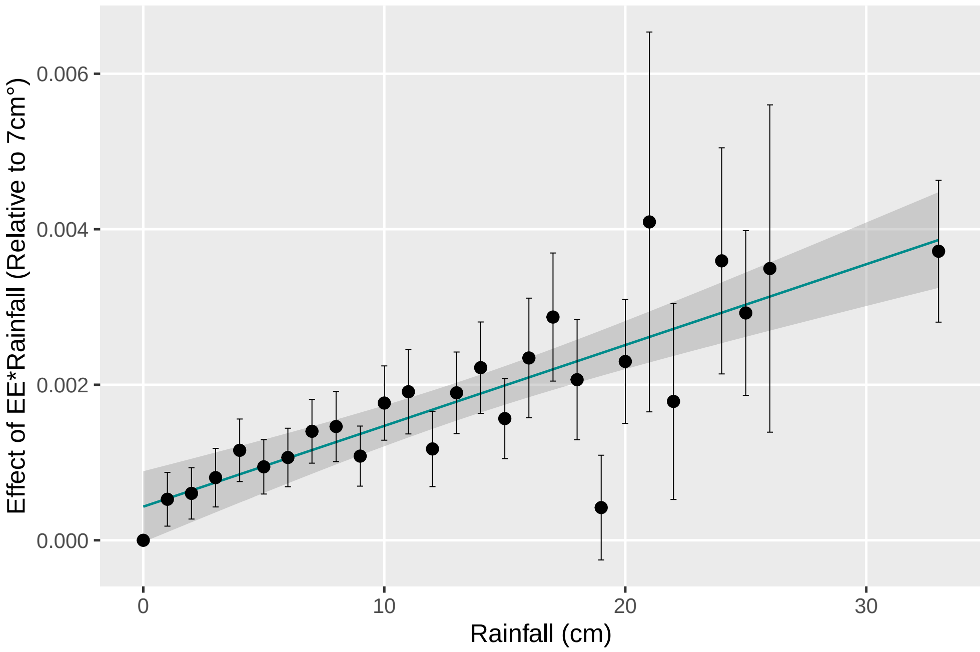
[17] We follow the binning strategy used by Busse et al. (2015).

Figure 3: EE valuation – Air temperature



Notes: This figure plots the coefficients and 95% confidence intervals for the interaction term EE*Temperature from Specification (2) across the air temperature range. Sale transactions are binned at $0.5C°$ intervals with $11C°$ as the holdout bin category (the average monthly air temperature in the data).
N=5,325,834.

Figure 4: EE Valuation – Rainfall



Notes: This figure plots the coefficients and 95% confidence intervals for the interaction term EE*Rainfall from Specification (2) across the rainfall range. Sale transactions are binned at 1*cm* intervals with 7*cm* as the holdout bin category (the average monthly rainfall in the data).
N=5,325,834.

4.1 Interaction effects in a regression kink design

In order to formally test the changes in the size of the effect that air temperature has on EE valuation at $6.5C^{\circ}$ and $17C^{\circ}$, we employ a regression kink design (RKD) as described by Nielsen et al. (2010) and Card et al. (2015). While the current literature on RKD deals with the identification and estimation of treatment effects when there is a change in the slope (i.e. a kink) of the running variable, we have adapted this framework to estimate treatment effects when there is a kink in the interaction term between the running variable and an independent variable.

Generally speaking, in our setup, the effect of an observable variable V (EE) on the outcome of interest Y (Price) is moderated by another observable variable X (Weather). This effect is captured through the moderation function $f(V, X)$, which is what we are ultimately interested in. The effect of $f(V, X)$ on Y is heterogeneous across the range of X: If the value of X is over a threshold X_T, then the moderating effect on V changes. The relationship between $f(V, X)$ and Y will then have a kink at $X = X_T$, and the corresponding change in slope can be estimated using a RKD.

In what follows, we first explain the RKD assumptions that must hold for identification of heterogeneous effects using interacted terms. We then present an estimator for obtaining empirical results and show the results of this method applied to the relationship between the EE rating of properties and air temperature as shown in Figure 3.

4.1.1 Identification

Formally, following the potential outcomes framework (Rubin 1974), we assume a random sample of observations where $Y \in \mathbb{R}$ represents the outcome of interest and $D \in \{0,1\}$ represents treatment status. The observed outcome is expressed as $Y = (1 - D) \cdot Y_0 + D \cdot Y_1$ where Y_0 and Y_1 are the potential outcomes with and without treatment respectively. The continuous observable variables $V \in \mathbb{R}$ and $X \in \mathbb{R}$ have an effect on Y. X also determines treatment status (i.e. is the running variable); if X is over a threshold value X_D then treatment is received: $D = \mathbb{1}(X \geq X_D)$. And, specific to our analysis, X also moderates the effect that V has on Y (i.e. X and V are interacted). We start with the following general specification, which allows for non-separability:

$$\begin{aligned}
(5) \qquad & Y = y(G, U) \\
& G = g(V, X, D \\
& D = d(X)
\end{aligned}$$

where $d(.)$ is a deterministic function of X with a kink at X_D. $g(.)$ is a function that captures the independent and interacted effects that X and V have on Y, which as explained above are heterogeneous on D. U represents the error term (which can enter the model non-separably). We are interested in the identification of the change of the moderating effect of X on V at the kink point X_D, which we denote as the estimand τ. The moderating effect is the cross-derivative of G with respect to V and X:

$$(6) \qquad \tau = \frac{\partial^2 g(v, 0, d_0)}{\partial v \partial t}, \text{ where } d_0 = d(X_D)$$

The existing literature on RKD (see Card et al. 2015 for a detailed discussion and review of previous literature) documents the assumptions necessary for identification of the effect of X on Y without interactions. We extend these assumptions for the case where Y depends on V, X and their interaction. All that is required are regularity and smoothness conditions for Y, X and V: Y is assumed to be a continuos function partially differentiable with respect to V, X and D and cross-partially differentiable with respect to V and X. Moreover, the partial derivative of D needs to be continuos at threshold X_D. Similarly, the effects of V, X and their interaction need to be continuos at X_D. Lastly, the conditional density of Y given V and X needs to be continuos at X_D (no sorting into treatment).

In order to estimate τ, G must be continuous and cross-differentiable with respect to V and X at X_D. This is an additional assumption that is introduced in our analysis over the standard RKD assumptions explained by Nielsen et al. (2010) and Card et al. (2015). Then, τ can be non-parametrically estimated as:

$$(7) \quad \tau = \frac{\lim\limits_{x_0 \to X_D^+} \frac{\partial^2 E[Y|V=v, X=x]}{\partial v \partial x}\Big|_{x=x_0} - \lim\limits_{x_0 \to X_D^-} \frac{\partial^2 E[Y|V=v, X=x]}{\partial v \partial x}\Big|_{x=x_0}}{\lim\limits_{x_0 \to X_D^+} \frac{\partial D(x)}{\partial x}\Big|_{x=x_0} - \lim\limits_{x_0 \to X_D^-} \frac{\partial D(x)}{\partial x}\Big|_{x=x_0}}$$

The numerator of the expression is the change in slope of the effect of the interaction between V and X on the conditional expectation of Y at the kink point $x = X_D$. The denominator is the change in the slope of the deterministic treatment function D at $x = X_D$.

A functional form with a derivative that is continuos at $x = 0$ must be assumed for the moderation function $f(V, X)$. If a multiplicative function is assumed, then as $\frac{\partial f(v,x)}{\partial x} = v$ the only additional condition for the identification of τ is that V must be continuos (i.e. without a jump) at $x = 0$. This additional condition ultimately translates into having to perform the same continuity tests for V as the ones for X.

4.1.2 Estimation and inference

Our RKD identification of interacted effects does not impose any parametric restrictions on $y(.)$. However, some assumptions are required to obtain empirical estimates of τ. Importantly, as shown before, $g(.)$ must be cross-differentiable with respect to V and X. If $y(.)$ and $g(.)$ are modelled as additive functions, and the interaction between V and X within $g(.)$ as a cross-product, then the estimation of τ can be obtained using local polynomial regressions (generalised for RKD in Card et al. 2015 and Calonico et al. 2014). We employ the following first-order specification:[18]

$$Y_i = \alpha + \beta V_i + \gamma X_i + \delta V_i \cdot X_i + D_i[\lambda + \mu V_i + \omega X_i + \theta V_i \cdot X_i] + \varepsilon_i \tag{8}$$

[18]We model V, X and $V \cdot X$ as a first order polynomial to simplify interpretation.

The coefficients of interest are δ, which captures the slope of the interacted effect of V and X when treatment is not received, and θ, which captures the additional effect when treatment is received. The coefficients γ, δ, μ and ω are necessary to prevent δ and θ from capturing the independent effects of V and X on Y, which are not the main focus of our analysis. Moreover, to improve the precision of the estimator (as explained by Calonico et al. 2019 for RDDs and RKDs), a vector of control covariates Z can be included in the regression as:

$$(9) \qquad Y_i = \alpha + \beta V_i + \gamma X_i + \delta V_i \cdot X_i + D_i[\lambda + \mu V_i + \omega X_i + \theta V_i \cdot X_i] + \boldsymbol{Z_i}\zeta + \varepsilon_i$$

The estimation of τ using a local polynomial regression will depend on the selection of the order of the polynomial, the kernel and the bandwidth (Card et al. 2015). If a first order polynomial with a uniform kernel is used then the local estimation of Specifications (8) and (9) can be obtained using OLS. The numerator for the estimation of τ in Equation (7) is the estimation for θ. Also, if X is exogenous to Y, as is the case in our analysis, then the denominator term is 1 and the estimator is just θ.

4.2 Heterogeneous weather effects on EE valuation

We now apply the identification and estimation strategy presented above to test for the different effects that severe and mild weather conditions have on EE valuation. Our outcome of interest is price per meter (Y), our running variable is air temperature (X) which determines treatment status (D) and also moderates the effect of the EE rating score (V) on price. Treatment (D) is received if air temperature (X) is above the threshold of interest (X_D), either $6.5C^\circ$ or $17C^\circ$. Appendix B shows that the variables used in our analysis (air temperature and EE rating) satisfy the identification conditions explained above.

Our formal estimates confirm the kinks in EE valuation across monthly mean air temperature that can be observed in Figure 7 at $6.5C^\circ$ and $17C^\circ$. Table 5 presents the estimates obtained using Specifications (8) and (9). Columns (1) to (3) present the results for the threshold at $6.5C^\circ$ and Columns (4) to (6) for the threshold at $17C^\circ$. Columns (1) and (4) show the estimates using Specification (8), which does not include any covariates. Columns (2) and (5) present the results of Specification (9) using the vector of covariates Zi (property characteristics, area FE, date FE, rainfall and rainfall interacted with the EE rating). Finally, Columns (3) and (6) add market-condition covariates (local market FE and local market interacted with the EE rating). Importantly, for Specification (9) – which includes all covariates and is depicted in Columns (3) and (6) – the estimates for the effect of the EE rating on price before crossing the threshold (coefficient β) are very close to those obtained using the pooled cross-sectional regression analysis from Section 3, and they do not change much after crossing the threshold (coefficient μ). This provides empirical evidence that the interaction terms in our RKD specification (coefficients δ and θ) are the ones that capture the changes in the moderating effect of the EE rating on price at the thresholds.

The estimates for our main parameter of interest, θ, are statistically significant at the 0.1% level and remarkably stable across all specifications. The stability of the results to the inclusion of covariates provides evidence that the relationship between the EE ratings and air temperature on the month the buying offer is made is not systematically correlated with any observable property characteristic in a way that would be of concern.

We start by discussing the results for the threshold at $17C^{\circ}$ using our most restrictive specification (Column 6). When the temperature is below $17C^{\circ}$, the coefficient for δ indicates that a $1C^{\circ}$ increase in air temperature reduces the effect of the EE rating on price by 0.01 percentage points. However, when the air temperature is higher than $17C^{\circ}$, the coefficient for θ shows that an increase of $1C^{\circ}$ reduces the effect of EE rating by much more, 0.046 percentage points (in addition to the 0.01 percentage points estimated for δ). With respect to the threshold at $6.5C^{\circ}$, when the temperature is lower than $6.5C^{\circ}$, for a $1C^{\circ}$ increase in air temperature the effect of the EE rating decreases by 0.024 percentage points (coefficient δ). When the threshold is crossed, the additional effect (captured by the estimate for coefficient θ) becomes positive, indicating a much lower effect of air temperature on EE valuation.

Appendix B presents and discusses a wide range of robustness checks including continuity tests for the EE rating, air temperature and price per meter (log) variables (as explained in the previous section) and different bandwidth sizes.

Table 5: RKD results

	$6.5C^{\circ}$			$17C^{\circ}$		
	(1)	(2)	(3)	(4)	(5)	(6)
EE Rating*Temperature*T [θ]	0.038^{***}	0.041^{***}	0.041^{***}	-0.076^{***}	-0.053^{***}	-0.053^{***}
	(0.011)	(0.006)	(0.006)	(0.021)	(0.010)	(0.010)
EE Rating*Temperature [δ]	-0.014	-0.022^{***}	-0.024^{***}	-0.016^{**}	-0.012^{***}	-0.012^{***}
	(0.008)	(0.005)	(0.005)	(0.006)	(0.003)	(0.003)
EE Rating*T [μ]	-0.060^{**}	-0.041^{***}	-0.038^{***}	-0.039	-0.016	-0.016
	(0.021)	(0.011)	(0.011)	(0.025)	(0.012)	(0.012)
EE Rating [β]	0.357^{***}	0.113^{***}	0.112^{***}	0.269^{***}	0.103^{***}	0.103^{***}
	(0.040)	(0.011)	(0.011)	(0.036)	(0.010)	(0.010)
Property Characteristics		Yes	Yes		Yes	Yes
Area FE		Yes	Yes		Yes	Yes
Date FE		Yes	Yes		Yes	Yes
Local Market FE			Yes			Yes
EE Rating*Local Market FE			Yes			Yes
RD Bandwidth	4	4	4	4	4	4
R-squared	0.023	0.715	0.715	0.061	0.729	0.729
Observations	2,494,385	2,494,385	2,494,385	1,951,386	1,951,386	1,951,386

Notes: Standard errors in parentheses. * significant at 5%; ** significant at 1% *** significant at 0.1%. Coefficients and standard errors have been multiplied by 100 to interpret them as percentage point increases. Standard errors clustered at the LAD level. The EE Rating ranges from 1 to 100. Temperature is measured in C° and Rainfall in *cm*. Property Characteristics FE include property type, tenure and number of rooms. Location FE include LAD and urban/rural classification. Date FE include sale year and month. Local Market FE add number of sales per month in the LAD (normalised and demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned). Columns (1) to (3) present the results for the kink at $6.5C^{\circ}$ and columns (4) to (6) for the kink at $17C^{\circ}$. Columns (1) and (4) show the results using Specification (8) which does not include covariates. Columns (2) and (5) use Specification (9) including the vector of baseline covariates. Columns (3) and (6) add controls for local market conditions.

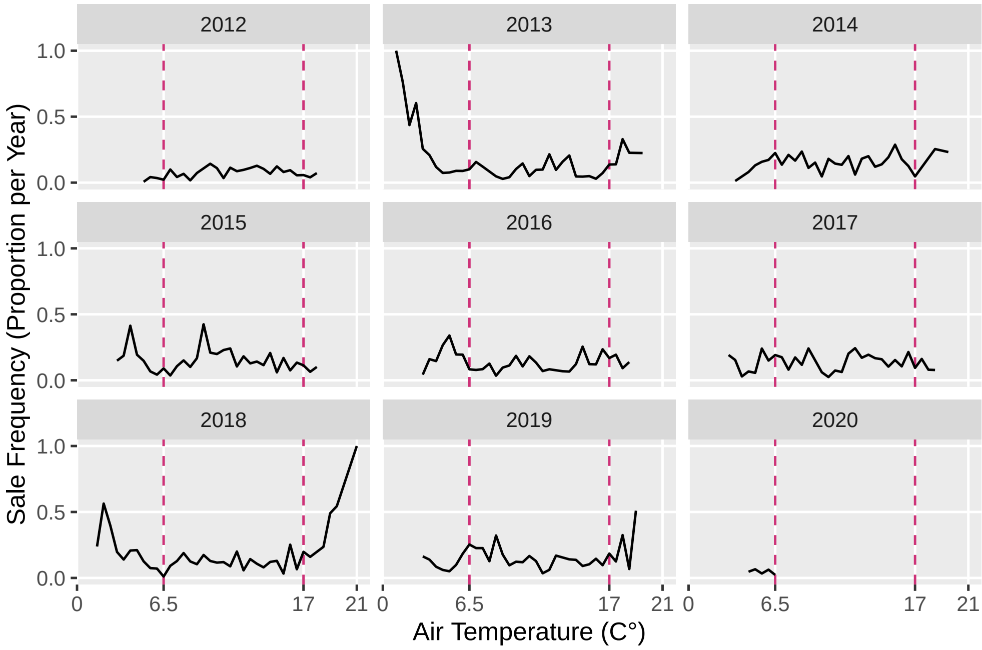
4.2.1 Extreme weather events and heterogeneity across regions

We show how the effect of air temperature on EE valuation changes considerably under severe weather conditions (very cold and very warm weather). This is important for policy making as extreme weather events cannot be easily predicted and there is ample evidence that they will only become more frequent due to global warming (Xu et al. 2018). For instance, as reported by the MET Office, the 10 warmest years on record in the UK have all occurred since 2002 (Kendon et al. 2019). The Summer of 2018 saw extremely warm temperatures and was registered as the warmest in England since records began in 1884 (Kendon et al. 2019). Similarly, severely cold temperatures occurred in the Winters of 2013 and 2018 and severely warm temperatures in the Summer of 2018. These events were recorded as extreme events by the UK MET Office (see Kendon & McCarthy 2015 and Kendon et al. 2019 for a detailed meteorological discussion). The Winter of 2013/2014 was recorded as the stormiest period in the UK during the last 20 years (Kendon & McCarthy 2015), while the Winter of 2018 saw extremely cold temperatures as a result of a polar continental air mass (Kendon et al. 2019), which prompted the media to dub this event as 'the beast from the east'. Figure 5 shows the average monthly air temperature for each calendar year.

Our analysis controls for the date of sale, and we demonstrate that the temperature effects we document are not driven by these extreme events by running our analysis excluding sales from 2013 and 2018 as part of our robustness checks (in Appendix B). Rather, our results highlight the importance of considering rapidly changing weather conditions in the design of household energy policies.

Similarly, not all regions in the UK experience the same weather conditions. Figure 6 shows the sale frequency (as proportions) across the air temperature range by region. The north of England experiences colder weather in general and thus it has a larger proportion of sales occurring in low temperatures. Conversely, the south and east of England experience warmer weather overall and thus a larger proportion of sales under high air temperature occur there. Our analysis controls for narrowly defined geographic areas (local authority districts) and their market conditions to show that our results are not specific to any of these areas. We also

Figure 5: Sale frequency proportion - Air temperature (by year)

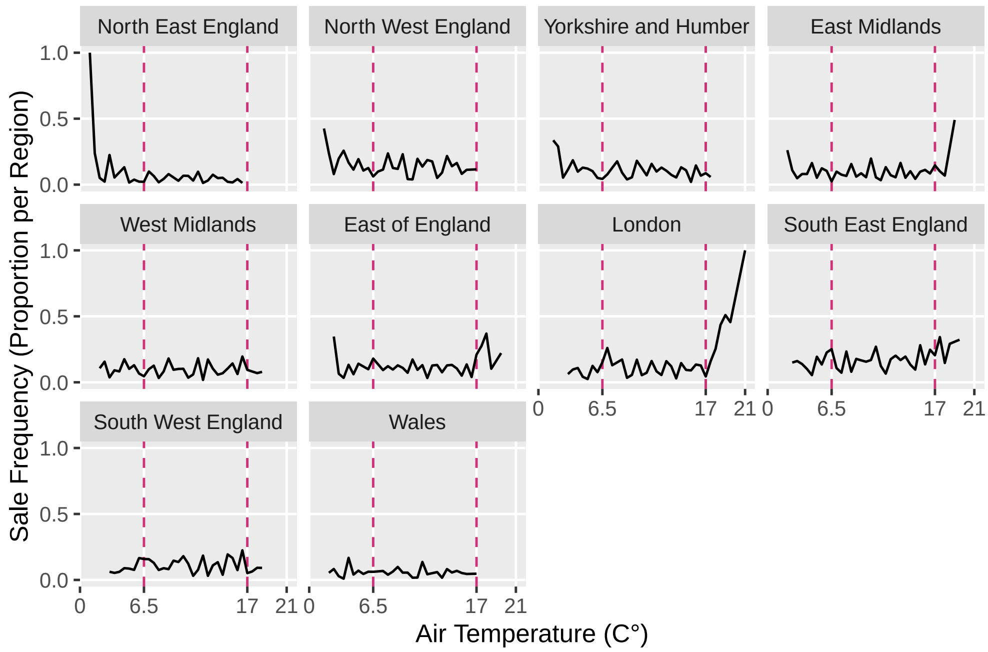


Notes: This figure plots sale frequency proportions across the air temperature range separately for each calendar year.
N=5,325,834.

show in Appendix B that our results hold even if we remove the regions with the highest proportions of sales under severely cold and warm weather (namely North East and London).

Our results show that policies aimed at increasing the EE of the housing stock should account for the fact that EE valuations are not homogenous across the country.

Figure 6: Sale frequency proportion - Air temperature (by region)



Notes: This figure plots sale frequency proportions across the air temperature range separately for each region.
N=5,325,834.

5 Discussion

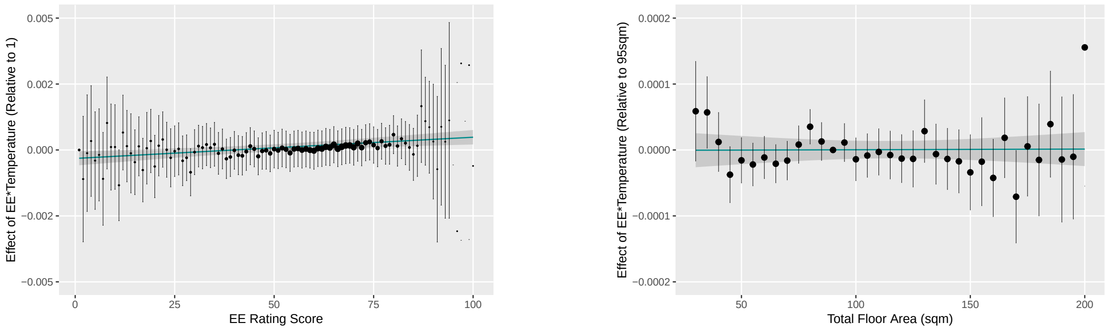
We start this section by showing that our results are unlikely to be driven by rational optimisation behaviour, namely optimising running fuel costs. We then proceed to discuss potential psychological mechanisms and biases that can explain the effects we identify.

5.1 Rational optimisation of running fuel costs

If current weather conditions were a good predictor of future weather conditions, then a possible explanation for our results would be that individuals value EE more in harsh weather conditions under the expectation of saving on future running energy costs. Higher EE translates to lower energy consumption while maintaining the same level of benefits from energy services. If running fuel cost optimisation was the mechanism behind the increased EE valuation we observe during colder months, then: (a) Current weather (at $t-1$) should be a good predictor of future weather so that estimating total energy consumption based on $t-1$ would be possible; and (b) the effect of weather conditions on EE valuation should be stronger for bigger properties and properties with lower EE ratings, as these incur in higher energy consumption and therefore have higher energy running costs.

With regards to (a), Figure 1 shows the mean air temperature for each calendar month. The climatic seasons (spring, summer, autumn and winter) are quite pronounced in the UK and the temperature transitions are smooth. Nonetheless, the speed at which temperatures change, shown by the different slopes of the temperature function in Figure 1 do not follow a pattern. Similarly, the maximum and minimum monthly temperatures for each year are not correlated to that of previous years. There is plenty of literature documenting the unpredictability of the weather (e.g. Palmer 2017, Bauer et al. 2015). Existing research shows that currently weather forecasts can be estimated with enough accuracy to be useful only up to 10 days in advance (Alley et al. 2019, Bauer et al. 2015). Thus, the weather conditions at time $t-1$ would provide additional information only for the subsequent two weeks. Energy costs would have to be extremely high for the price

Figure 7: EE valuation – Air temperature



(a) Across EE ratings

(b) Across property sizes

Notes: This figure plots the coefficients and 95% confidence intervals for the interaction term EE*Temperature from Specification 2 across EE ratings and property sizes. Panel (a) shows the average effects across the EE rating range (from 1 to 100) binned at each EE rating score, with EE rating 1 as the bin hold-out category. Panel (b) shows the average effects across property sizes, measured as the total floor area in square-meters (sqm), using 5sqm bins and the 95sqm bin as the hold-out category (the average in the data).
N=5,325,834.

premiums we estimate in Sections 3 and 4 to justify the additional expenditure for such a short period.

Regarding (b), we find that the relationship between air temperature and EE valuation is mostly constant across EE ratings and property sizes. Figure 7 shows the relationship between our estimated parameter for EE*Air temperature (parameter θ from Specification 2) across the full EE rating scale (panel a) and across properties of different sizes (panel b). There is little variation across EE ratings, and the trend is slightly positive, contrary to the prediction for optimization of energy costs. The effect across properties of different sizes is even smaller and the general trend is flat without statistically significant differences.

Neither prediction (a) or (b) holds, therefore our results from Sections 3 and 4 are not indicative of buyers trying to optimise on running energy costs. In the next section we argue that they seem to bee driven by psychological mechanisms instead.

5.2 Psychological mechanisms

In this section we discuss potential psychological mechanisms that can explain our results. We model and study projection bias and overinference bias within an intertemporal valuation framework (Ericson & Laibson 2019), and salience within a limited attention framework (Gabaix 2019). Our results from Sections 3 and 4 are consistent with these three biases, and it is difficult to differentiate them using solely sale transaction data, thus we do not advocate for any mechanisms as the main driver. Regardless of which psychological mechanisms are contributing to the price effects we find, a (bounded) rational individual will attempt to correct their mistakes once they become aware of them. In the last part of this section we show evidence suggesting that some sellers are taking corrective action.

5.2.1 Intertemporal valuation and biased future utility maximisation

To simplify our discussion, we focus on the intertemporal valuation of EE by buyers who intend to live in the property. Buyers who intend to rent or resell the property derive less direct benefits from EE, and thus we anticipate that the effect of external factors such as the weather on EE valuation will be lower (e.g. they do not have to worry about paying higher energy bills during a particularly cold winter).[19]

[19] While buyers who intend to rent the property may be influenced by the weather on how much they will be able to charge (e.g. advertise a property as 'cosy'), we expect the effect to be lower than for buyers who intend to live in the property.

As mentioned before, in asset and investment markets, the valuation of a product and its features needs to account for the total anticipated utility across the ownership time-frame. Importantly, the utility derived at each time period will depend on the state of the world at the time (i.e. state-dependent utility). As future states cannot be predicted with certainty, the expected utility for each time period also depends on the (a priori) probabilities of the different states occurring (i.e. a decision about the future needs to be made under uncertainty).

The payoff obtained from owning a property with a specific EE level is a function of the energy services consumed (e.g. room temperature, water temperature and lighting) and the cost of the fuels these services require (e.g. electricity and/or gas). Assuming time-consistent preferences, individuals have an optimal energy services consumption that does not change over time (resulting from consumption smoothing).[20] The expected utility derived at each time period depends on the payoff function and the current state of the world, which, as mentioned above, is uncertain.[21] The state of the world depends on exogenous factors such as the weather. For instance, there can be uncertainty about the minimum temperatures of future winters. Then, from a classic expected-utility-maximisation perspective the EE valuation of a fully rational individual (based on the model documented by Rabin 2002*b* and DellaVigna 2009) is given by:

[20] For simplicity, we will not consider budget constraints or changing preferences, such as environmentally concerned lower energy services consumption. Nonetheless, if preferences move in the direction of reducing energy consumption then higher EE will be preferred. The effects of weather on EE valuation should then be lower since it will have a lower influence on energy consumption and comfort.

[21] The payoff can be adjusted for the depreciation of the EE features across time.

$$(10) \qquad U_e = \sum_{t=T_0}^{T_0+T_N} \delta^{t-T_0} \sum_{s_t \in S_t} p(s_t) u(x_t^e | s_t)$$

$$x_t^e = x(c_t^e, f_t)$$

$$s_t = s(w_t)$$

Where U_e is the energy-efficiency related utility derived from ownership of a property with EE rating e. Utility is accumulated in all ownership time periods $t \in [T_0, T_0 + T_N]$ (we use months as the unit of t as fuels such as electricity are typically invoiced monthly). The parameter $\delta \in [0, 1]$ is the (time consistent) discount factor. For each time period t, the expected utility is obtained from all the possible states $s_t \in S_t$ and their probabilities of occurring. The probability that state s_t occurs is given by $p(s_t)$. The payoff of having a property with an EE rating e at time t is x_e^t, and the utility derived from payoff x_e^t given state s_t is $u(x_e^t | s_t)$. The payoff x_e^t depends on the energy-services consumption provided the property has an EE rating e and the cost of fuel is f_t at time t.[22] Higher EE increases the payoff by decreasing energy services consumption. We model the state of the world s_t as a function of weather conditions w_t at time t. As the EE rating of a property is exclusively derived from the energy requirements for heating, lighting and hot water, we assume the main external factor affecting U_e to be the weather w_t.

Importantly, in the UK housing market, EE valuation happens at $T_0 - 1$, one

[22] We can extend the model to account for accumulated EE feature depreciation e_t^d entering function $f(.)$, but we choose to keep the model simple to help with our discussion of potential mechanisms for EE valuation.

month before ownership starts. As explained in Section 2, it normally takes over a month from the moment an offer is made to the completion of the sale transaction; only then is the new owner able to either move in, rent out or resell the property. There are no payoffs at time $T_0 - 1$, and thus the weather conditions at $T_0 - 1$ do not enter the valuation function directly. We now proceed to discussing possible explanations for why weather conditions at $T_0 - 1$ can have the effects that we document in Sections 3 and 4.

State-dependent preferences and projection bias

Individuals may exhibit state-dependent preferences where their utility evaluations depend on the state they are experiencing at the time. For instance, room temperature preferences may be different if an individual is feeling very warm or very cold (analogous to the example used by Loewenstein et al. 2003 where individuals order more food at the beginning of a meal if they are feeling particularly hungry). Intuitively, if individuals are feeling very warm during a particularly hot summer, they will prefer cold indoor temperatures and their utility evaluations for heating services will be very low. Furthermore, these state dependent preferences can be projected into the future, thus reducing the expected utility derived from heating services over the whole ownership period and consequently influencing the total EE valuation. This behavioural bias, expecting future preferences to be similar to current ones when contextual factors (i.e. the state of the world) may be different, is referred to as projection bias in the literature (Loewenstein et al. 2003). In our model, the weather conditions at time $T_0 - 1$ (when the buying decision was made) do not enter the EE valuation function of a rational agent as they will have no bearing on the experienced benefits derived from EE during ownership. An individual exhibiting projection bias would have the following EE valuation function (incorporating modelling concepts from Loewenstein et al. 2003):

$$U_e = \sum_{t=T_0}^{T_0+T_N} \delta^{t-T_0} \sum_{s_t \in S_t} p(s_t)\hat{u}(x_t^e|s_t, s_{T_0-1}) \tag{11}$$

$$\hat{u}(x_t^e|s_t, s_{T_0-1}) = (1-\alpha)u(x_t^e|s_t) + \alpha u(x_t^e|s_{T_0-1})$$

Now the predicted experienced utility function $\hat{u}(.)$ takes into account not only the state of the world at time t but also the state of the world at time $T_0 - 1$. The parameter $\alpha \in [0,1]$ represents the extent of the bias. If $\alpha = 0$, the individual does not exhibit projection bias and the utility evaluation is the same as before. If $\alpha > 0$, the predicted future utility evaluation is influenced by the present state (e.g. weather conditions).

Overinference and future weather conditions

We can see graphically in Figure 1 that the current weather conditions are not a good predictor for future weather conditions. As mentioned above, there is plenty of literature documenting the unpredictability of the weather (e.g. Palmer 2017, Bauer et al. 2015). Nonetheless, previous research (e.g. Rabin 2002*a*) has shown that people make overinferences from a small number of observations. A potential explanation for the results we observe is that people may overweight the probability of certain weather conditions happening in the future based on the weather they observe in the short sequence of months prior to their purchase. In other words, individuals use the weather conditions of the past few months to make predictions about long term weather trends. We can extend our model to include overinference as follows:

$$U_e = \sum_{t=T_0}^{T_0+T_N} \delta^{t-T_0} \sum_{s_t \in S_t} \hat{p}(s_t|s_{t-1},s_{t-2},...)u(x_t^e|s_t) \tag{12}$$

Where the probability distribution function $\hat{p}(.)$ is not i.i.d. and depends on the previous observed states of the world.

5.2.2 Limited attention and salience

Another potential explanation for our results is that weather conditions will influence the salience of EE during the purchasing process. Intuitively, while experiencing cold weather, individuals will pay more attention to the EE rating of properties while they search for houses. Current weather will then influence the weight that EE has on the final sale price of a property. Previous research (e.g. Sejas-Portillo et al. 2020, Myers 2019) shows that limited attention plays an important role in the understanding of energy labels and energy costs in the housing market. A simple model where the effect of EE on price depends on the weather can be expressed as:

$$P_i = \tilde{v}(e_i, w_t^r) + f(c_i, a_l, m_t^l) + \varepsilon_i \tag{13}$$

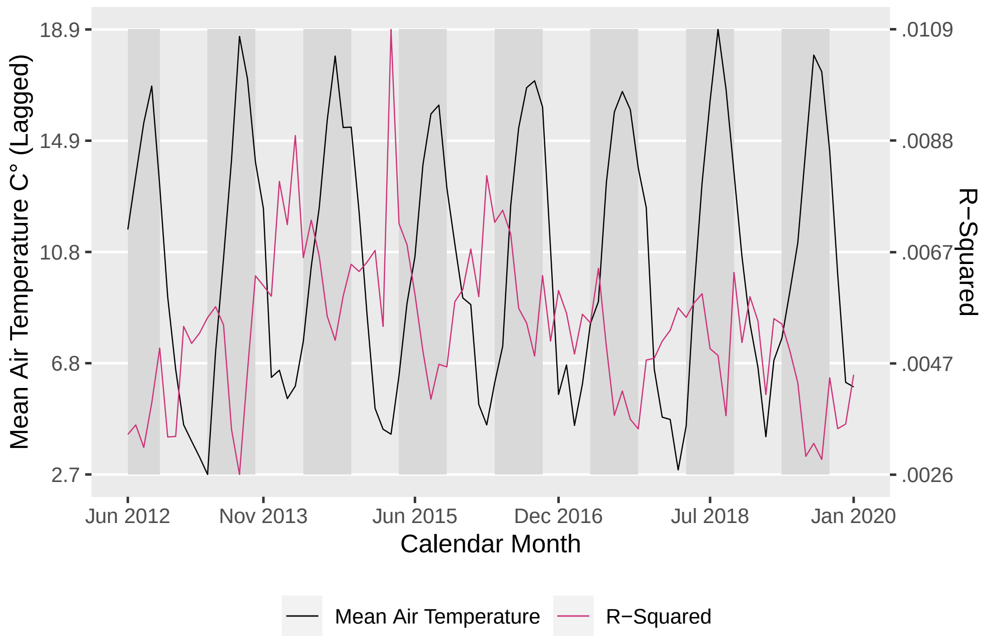
$$\tilde{v}(e_i, w_t^r) = v(e_i) * \theta g(w_t^r)$$

Where the function $\tilde{v}(.)$ captures the observed (final) valuation of the EE of property i, and depends on its EE rating e_i and weather conditions w_t^r in region r at time t. The function $f(.)$ captures all of the other property features that influence the selling price, including property characteristics c_i (e.g. number of rooms), area amenities a_l for location l (e.g. number of nearby parks) and market conditions for the location at the time of the valuation m_t^l (e.g. hotness of the market).

The observed valuation of EE $\tilde{v}(e_i, w_t^r)$ depends on the true valuation of EE, $v(e_i)$, which is weighted by the function $g(w_t^r)$ that captures the effect of weather conditions (at the time a buying decision is made) on the salience of EE. Function $g(.)$ can produce values between $[0, 1]$: If the weather does not influence the salience of EE then $g(.) = 1$. If weather conditions do influence the salience of EE, then $g(.) \neq 1$. For example, during a very warm summer, $g(.)$ may be close to 0, meaning that individuals place very little importance to the EE rating of the property during the buying process.

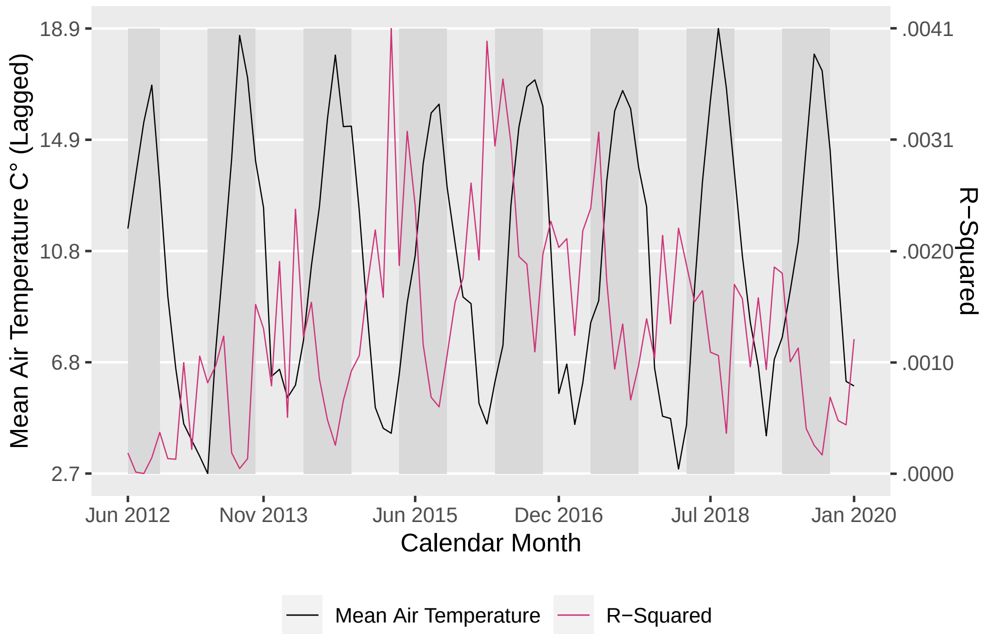
To empirically investigate the role that attention to EE information plays in the sale price of a property, we analyse how much of the variability in the final sale price can be attributed to the variability in EE rating. If individuals pay more attention to EE during colder weather then the variability of the coefficient for the EE rating will be lower than during warmer weather. Figure 8 shows the estimate for the coefficient of determination R^2 of a regression of the EE rating on price per meter (log). To account for the effect of properties of different characteristics and locations, Figure 9 shows the same relationship for a regression where the dependent variable is the residualised price per meter (log) after controlling for property characteristics, location, date and market conditions (the same covariates used in Specification 2). A clear pattern is visible in both figures: As temperature increases, R^2 decreases, which supports the notion that salience plays a role for the results we document.

Figure 8: Air remperature - R^2 for EE rating on price



Notes: This figure plots the coefficient of determination R^2 from a regression of EE rating on price per meter (log) for each calendar month and the average monthly mean air temperature for the UK. The mean air temperature is lagged by one month to account for the time between the date a sale is agreed upon and the date it is completed.
N=5,325,834.

Figure 9: Air temperature - R^2 for EE rating on price residuals



Notes: This figure plots the coefficient of determination R^2 from a regression of EE rating on price residuals for each calendar month and the average monthly mean air temperature for the UK. The price residuals are obtained from a regression on price per meter (log) of property characteristics, location, date and market conditions. The mean air temperature is lagged by one month to account for the time between the date a sale is agreed upon and the date it is completed.
N=5,325,834.

5.2.3 Utility maximisation corrections

If (bounded) rational individuals make incorrect predictions about future utility – whether these are due to projection bias, overinference, salience or another mechanism – they will attempt to take corrective action once they realise their mistake (Conlin et al. 2007). Within the context of our analysis, if individuals purchased a property during a hot summer and mistakenly predicted low future utility from EE features (e.g. they projected their current heating preferences), once winter arrives they should realise their misprediction and invest to increase the EE of the property. While our dataset does not allow us to observe all of the EE investments made to the properties (since it is not required to commission a new EPC or energy audit after an improvement), we can analyse the subset of properties that were sold more than once and where the EE rating reported for the resale increased.

To test the presence of this behaviour empirically we run a simple regression on properties that were sold more than once (1,329,057 observations) where the dependent variable is an indicator of whether the EE rating has increased since the previous sale (i.e. a linear probability model). The independent variables are – as before – the EE rating, baseline covariates (property characteristics, location and date), local market conditions and lagged weather conditions. The results show that for each additional C° in air temperature during the month the purchase decision was made, the probability of investing in EE increases by 0.145 (SE 0.141) percentage points. And for each additional cm of rainfall the probability decreases by -0.015 (SE 0.020) percentage points. The directions of the effects are as expected and their magnitudes are considerable. Our estimations from Sections 3 and 4 show that buyers undervalue EE when the weather is warm (or at the minimum that they value it less than if the weather was colder). If they realise their mistake when the weather gets cold they are more likely to invest in EE, hence the positive sign of the coefficient in the regression. Rainfall works in the opposite direction, hence the negative sign of the coefficient. These results suggest that at least some buyers take corrective action once they realise they made a mistaken utility prediction.

6 Conclusion

We present evidence that weather conditions, at the time a buying decision is made, can disproportionately influence the valuation of EE in the UK housing market. We find that EE valuations made during rough weather (e.g. cold and/or rainy) are higher than those made under favourable weather (e.g. warm and/or dry). For example, on average, we document that a 10 point increase in the EE rating of a property leads to a sale price increase of 1.687 percentage points (£4,461 at average sale prices) if the air temperature was $5C^{\circ}$ on the month the buying offer was made. However, the same 10 point increase in EE rating would lead to an increase of only 0.385 percentage points (£1,018 at average sale prices) if the temperature was $20C^{\circ}$. Similarly, if the total monthly rainfall was $1cm$ during the month the buying decision was made, a 10 point increase in the EE rating leads, on average, to a 0.552 percentage points (£1,459.71) increase in price. If the total monthly rainfall was $15cm$, the price increase is much higher at 1.914 percentage points (£5,061.68). Using a novel estimator (within a regression kink design framework) we show that the relationship between air temperature and EE valuation is kinked at $6.5C^{\circ}$ and $17C^{\circ}$. These kinks are expected as individuals are more sensitive to severe temperatures (either cold or warm). We also discuss the importance of these results given the increase in the frequency of extreme weather events due to climate change and the varying weather conditions across regions in England and Wales.

We show that the effects we document do no seem to be driven by rational optimisation of running fuel costs. Rather, we model and discuss potential psychological mechanisms and biases that can explain our results. We model EE valuations within an intertemporal utility maximisation framework (Ericson & Laibson 2019) to discuss projection bias (Loewenstein et al. 2003) and overinference (Rabin 2002*a*), and within a limited attention framework (Gabaix 2019) to discuss salience. We do not argue for any of these biases as the main driver since our transactional data does not allow us to differentiate between them. Nonetheless, we present evidence suggesting that some individuals display (bounded) rational behaviour and take corrective action (in the form of future EE investments) once they realise their mistaken (biased) utility predictions.

As mentioned earlier, policies that fail to consider the effects of relevant external factors – such as the weather for EE – can be difficult to predict and manage. Moreover, in the case of the UK housing market, there is a positive overall welfare effect of EE improvements, in the form of reduced housing energy consumption contributing to mitigating climate change. In the UK, EE is most beneficial during winter to keep properties warm,[23] thus a low-cost informational intervention where property buyers are reminded about winter temperatures and rainfall levels can influence summer purchases (towards higher EE valuation) while retaining the existing effect on winter purchases. Another informational intervention can provide statistics about the increasing incidence of extreme weather events to buyers, since, as described in Section 4.2.1, they are likely to become more frequent. These informational cues can be included, for instance, as part of the mandatory energy performance certificate (EPC) shown to all potential buyers. We argue against including comparative seasonal cost information in this specific scenario (e.g. including comparisons of energy costs during winter and summer), since it could have the drawback of hinting at overpriced energy costs during winter (e.g. buy-

[23]In other countries EE is most beneficial during summer to keep properties cool.

ers in winter thinking that their overall costs will be lower in summer). Having differentiated policies for different regions in the UK can also be beneficial. For example, we show in Section 4.2.1 that severe cold weather is more likely in certain regions, thus informational policies can be prioritised in these regions and rolled out as needed to the others. Further research involving field experiments (e.g. randomized controlled trials RCTs) can greatly inform policy about the most effective interventions.

Continuing with this line of research, it is important to disentangle the effects of projection bias, overinference and salience. Distinguishing between these mechanisms in the field is difficult (Ericson & Laibson 2019) as they influence decisions in the same manner, laboratory experiments can be performed to this end. Finally, the welfare implications of our findings can be investigated further, specifically how the effects we document compare to current and predicted energy costs and EE improvement costs to provide a comprehensive cost-benefit analysis of implementing de-biasing interventions.

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Appendix A Measures of local market conditions

A.1 Local market sale intensity

Our measure of local market sale intensity is computed per LAD per month. It represents the deviation from the LAD average monthly sale frequency. We compute it as:

$$M_{l,t}^{F} = F_{l,t} - \frac{\sum_{i=1}^{T} F_{l,t_i}}{T}$$

Where $M_{l,t}^{F}$ is our measure of local market sale intensity M^F for LAD l and month t. $F_{l,t}$ is the frequency of sales for LAD l and month t. T is the total number of months in out dataset. And $\sum_{i=1}^{T} F_{l,t_i}$ is the sum of the LAD frequency of sales for all months.

A.2 Local market price intensity

Our measure of local market price intensity is computed per LAD per month. It represents the deviation from the LAD average monthly price. To make this measure comparable across LADs and months, we need to detrend prices (to remove inflationary effects) and normalise the measure (since the price level of properties is not homogeneous across LADs – e.g. the price level of LADs in London is a lot higher than the price level of LADs in the North East).

We first detrend the prices at the year level by obtaining the residuals from a regression of price per meter (log) on the sale year as a categorical variable.

$$P_i = \alpha + \beta Y_i + \varepsilon_i$$

$$P_i^R = \varepsilon_i$$

Where P_i is the sale price per meter (log) of property i, Y_i is the year when property i was sold (as a categorical variable) and ε_i the portion of price that cannot be explained by the variability of the year dummies i.e. the price residual for property i we denote as P_i^R.

We then demean and normalise the price residuals:

$$M_{l,t}^P = \frac{\overline{P^R}_{l,t} - \frac{\sum_{i=1}^{T} \overline{P^R}_{l,t_i}}{T}}{\frac{\sum_{i=1}^{T} \overline{P^R}_{l,t_i}}{T}}$$

Where $M_{l,t}^P$ is our measure of local market price intensity M^P for LAD l and month t. $\overline{P^R}_{l,t}$ is the average price residuals for LAD l and month t. T is the total number of months in out dataset. And $\sum_{i=1}^{T} \overline{P^R}_{l,t_i}$ is the sum of the LAD average price residuals for all months.

Appendix B Robustness analysis results

Further robustness checks available from the authors upon request.

B.1 Cross-sectional analysis

Table B1: Effect of weather conditions on EE valuation (UK wide weather data)

	(1)	(2)	(3)	(4)
Energy Efficiency	0.119***	0.119***	0.119***	0.119***
	(0.009)	(0.009)	(0.009)	(0.009)
Temperature		−6.153***	−6.147***	−6.557***
		(0.182)	(0.182)	(0.195)
Rainfall		−0.981***	−0.978***	−1.194***
		(0.105)	(0.105)	(0.127)
EE*Temperature			−0.004***	−0.004***
			(0.000)	(0.000)
EE*Rainfall			−0.001***	−0.001***
			(0.000)	(0.000)
Property Characteristics	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Local Market FE				Yes
EE*Local Market FE				Yes
R-squared	0.721	0.721	0.721	0.721
Observations	5,325,834	5,325,834	5,325,834	5,325,834

Notes: Standard errors in parentheses. * significant at 5%; ** significant at 1% *** significant at 0.1%. Coefficients and standard errors have been multiplied by 100 to interpret them as percentage point increases. Standard errors clustered at the LAD level. The EE Rating ranges from 1 to 100. Temperature is measured in C° and Rainfall in *cm*. Property Characteristics FE include property type, tenure and number of rooms. Location FE include LAD and urban/rural classification. Date FE include sale year and month. Local Market FE add number of sales per month in the LAD (normalised and demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned). Column (1) presents the results of a regression of EE rating and baseline covariates on price-per-meter (log). Column (2) adds weather conditions on the month prior to the sale. Column (3) shows the results of Specification (1). Column (4) shows the results of Specification (2).

Table B2: Effect of weather conditions on EE valuation
(Excluding properties sold more than once)

	(1)	(2)	(3)	(4)
Energy Efficiency	0.090***	0.090***	0.089***	0.089***
	(0.009)	(0.009)	(0.009)	(0.009)
Temperature		0.135*	0.169*	0.022
		(0.068)	(0.069)	(0.091)
Rainfall		−0.007	−0.004	−0.006
		(0.015)	(0.015)	(0.015)
EE*Temperature			−0.007***	−0.009***
			(0.001)	(0.001)
EE*Rainfall			0.009***	0.009***
			(0.002)	(0.002)
Property Characteristics	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Local Market FE				Yes
EE*Local Market FE				Yes
R-squared	0.725	0.725	0.725	0.725
Observations	3,530,595	3,530,595	3,530,595	3,530,595

Notes: Standard errors in parentheses. * significant at 5%; ** significant at 1% *** significant at 0.1%. Coefficients and standard errors have been multiplied by 100 to interpret them as percentage point increases. Standard errors clustered at the LAD level. The EE Rating ranges from 1 to 100. Temperature is measured in C° and Rainfall in cm. Property Characteristics FE include property type, tenure and number of rooms. Location FE include LAD and urban/rural classification. Date FE include sale year and month. Local Market FE add number of sales per month in the LAD (normalised and demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned). Column (1) presents the results of a regression of EE rating and baseline covariates on price-per-meter (log). Column (2) adds weather conditions on the month prior to the sale. Column (3) shows the results of Specification (1). Column (4) shows the results of Specification (2).

Table B3: Effect of weather conditions on EE valuation (2-month weather lag)

	(1)	(2)	(3)	(4)
Energy Efficiency	0.119***	0.119***	0.118***	0.118***
	(0.009)	(0.009)	(0.009)	(0.009)
Temperature		0.244***	0.280***	0.147
		(0.069)	(0.070)	(0.080)
Rainfall		−0.008	−0.005	−0.009
		(0.015)	(0.015)	(0.014)
EE*Temperature			−0.008***	−0.008***
			(0.001)	(0.001)
EE*Rainfall			0.010***	0.010***
			(0.002)	(0.002)
Property Characteristics	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Local Market FE				Yes
EE*Local Market FE				Yes
R-squared	0.721	0.721	0.721	0.721
Observations	5,325,834	5,325,834	5,325,834	5,325,834

Notes: Standard errors in parentheses. * significant at 5%; ** significant at 1% *** significant at 0.1%. Coefficients and standard errors have been multiplied by 100 to interpret them as percentage point increases. Standard errors clustered at the LAD level. The EE Rating ranges from 1 to 100. Temperature is measured in C° and Rainfall in cm. Property Characteristics FE include property type, tenure and number of rooms. Location FE include LAD and urban/rural classification. Date FE include sale year and month. Local Market FE add number of sales per month in the LAD (normalised and demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned). Column (1) presents the results of a regression of EE rating and baseline covariates on price-per-meter (log). Column (2) adds weather conditions on the month prior to the sale. Column (3) shows the results of Specification (1). Column (4) shows the results of Specification (2).

Table B4: Effect of weather conditions on EE valuation (3-month weather lag)

	(1)	(2)	(3)	(4)
Energy Efficiency	0.119^{***}	0.119^{***}	0.118^{***}	0.118^{***}
	(0.009)	(0.009)	(0.009)	(0.009)
Temperature		0.800^{***}	0.831^{***}	0.661^{***}
		(0.081)	(0.081)	(0.106)
Rainfall		-0.108^{***}	-0.104^{***}	-0.108^{***}
		(0.012)	(0.012)	(0.013)
EE*Temperature			-0.006^{***}	-0.007^{***}
			(0.001)	(0.001)
EE*Rainfall			0.011^{***}	0.011^{***}
			(0.002)	(0.002)
Property Characteristics	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Local Market FE				Yes
EE*Local Market FE				Yes
R-squared	0.721	0.721	0.721	0.721
Observations	5,325,834	5,325,834	5,325,834	5,325,834

Notes: Standard errors in parentheses. * significant at 5%; ** significant at 1% *** significant at 0.1%. Coefficients and standard errors have been multiplied by 100 to interpret them as percentage point increases. Standard errors clustered at the LAD level. The EE Rating ranges from 1 to 100. Temperature is measured in C° and Rainfall in cm. Property Characteristics FE include property type, tenure and number of rooms. Location FE include LAD and urban/rural classification. Date FE include sale year and month. Local Market FE add number of sales per month in the LAD (normalised and demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned). Column (1) presents the results of a regression of EE rating and baseline covariates on price-per-meter (log). Column (2) adds weather conditions on the month prior to the sale. Column (3) shows the results of Specification (1). Column (4) shows the results of Specification (2).

B.2 RKD analysis

Table B5: RKD results
(Excluding sales from 2013 and 2018)

	6.5C°			17C°		
	(1)	(2)	(3)	(4)	(5)	(6)
EE Rating*Temperature*T [θ]	0.073^{***}	0.070^{***}	0.069^{***}	-0.067^{*}	-0.074^{***}	-0.072^{***}
	(0.015)	(0.009)	(0.009)	(0.030)	(0.016)	(0.015)
EE Rating*Temperature [δ]	-0.056^{***}	-0.054^{***}	-0.053^{***}	-0.018^{*}	-0.020^{***}	-0.021^{***}
	(0.013)	(0.008)	(0.008)	(0.008)	(0.004)	(0.004)
EE Rating*T [μ]	0.005	0.002	0.003	-0.164^{***}	-0.025	-0.026
	(0.024)	(0.014)	(0.014)	(0.032)	(0.015)	(0.015)
EE Rating [β]	0.310^{***}	0.072^{***}	0.073^{***}	0.269^{***}	0.089^{***}	0.088^{***}
	(0.042)	(0.015)	(0.015)	(0.038)	(0.011)	(0.011)
Rainfall		Yes	Yes		Yes	Yes
EE Rating*Rainfall		Yes	Yes		Yes	Yes
Property Characteristics		Yes	Yes		Yes	Yes
Area FE		Yes	Yes		Yes	Yes
Date FE		Yes	Yes		Yes	Yes
Local Market FE			Yes			Yes
EE Rating*Local Market FE			Yes			Yes
RD Bandwidth	4	4	4	4	4	4
R-squared	0.034	0.718	0.718	0.096	0.732	0.733
Observations	1,907,755	1,907,755	1,907,755	1,464,303	1,464,303	1,464,303

Notes: Standard errors in parentheses. * significant at 5%; ** significant at 1% *** significant at 0.1%. Coefficients and standard errors have been multiplied by 100 to interpret them as percentage point increases. Standard errors clustered at the LAD level. The EE Rating ranges from 1 to 100. Temperature is measured in C° and Rainfall in *cm*. Property Characteristics FE include property type, tenure and number of rooms. Location FE include LAD and urban/rural classification. Date FE include sale year and month. Local Market FE add number of sales per month in the LAD (normalised and demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned). Columns (1) to (3) present the results for the kink at 6.5C° and columns (4) to (6) for the kink at 17C°. Columns (1) and (4) show the results using Specification (8) which does not include covariates. Columns (2) and (5) use Specification (9) including the vector of baseline covariates. Columns (3) and (6) add controls for local market conditions.

Table B6: RKD results
(Excluding sales from the North East and London Regions)

	$6.5C^{\circ}$			$17C^{\circ}$		
	(1)	(2)	(3)	(4)	(5)	(6)
EE Rating*Temperature*T [θ]	0.033***	0.027***	0.027***	−0.067***	−0.039***	−0.040***
	(0.009)	(0.005)	(0.005)	(0.016)	(0.009)	(0.009)
EE Rating*Temperature [δ]	−0.017*	−0.012***	−0.014***	−0.024***	−0.011***	−0.010***
	(0.007)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)
EE Rating*T [μ]	−0.040**	−0.029***	−0.026**	−0.006	−0.016	−0.016
	(0.014)	(0.009)	(0.009)	(0.027)	(0.012)	(0.012)
EE Rating [β]	0.362***	0.119***	0.117***	0.266***	0.101***	0.101***
	(0.037)	(0.010)	(0.011)	(0.033)	(0.011)	(0.011)
Rainfall		Yes	Yes		Yes	Yes
EE Rating*Rainfall		Yes	Yes		Yes	Yes
Property Characteristics		Yes	Yes		Yes	Yes
Area FE		Yes	Yes		Yes	Yes
Date FE		Yes	Yes		Yes	Yes
Local Market FE			Yes			Yes
EE Rating*Local Market FE			Yes			Yes
RD Bandwidth	4	4	4	4	4	4
R-squared	0.017	0.637	0.637	0.034	0.644	0.644
Observations	2,128,147	2,128,147	2,128,147	1,628,100	1,628,100	1,628,100

Notes: Standard errors in parentheses. * significant at 5%; ** significant at 1% *** significant at 0.1%. Coefficients and standard errors have been multiplied by 100 to interpret them as percentage point increases. Standard errors clustered at the LAD level. The EE Rating ranges from 1 to 100. Temperature is measured in C° and Rainfall in cm. Property Characteristics FE include property type, tenure and number of rooms. Location FE include LAD and urban/rural classification. Date FE include sale year and month. Local Market FE add number of sales per month in the LAD (normalised and demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned). Columns (1) to (3) present the results for the kink at $6.5C^{\circ}$ and columns (4) to (6) for the kink at $17C^{\circ}$. Columns (1) and (4) show the results using Specification (8) which does not include covariates. Columns (2) and (5) use Specification (9) including the vector of baseline covariates. Columns (3) and (6) add controls for local market conditions.

Table B7: RKD results
(Bandwidth of 3)

	$6.5C^{\circ}$			$17C^{\circ}$		
	(1)	(2)	(3)	(4)	(5)	(6)
EE Rating*Temperature*T [θ]	0.101^{***}	0.081^{***}	0.080^{***}	-0.054^{**}	-0.033^{***}	-0.033^{***}
	(0.018)	(0.008)	(0.008)	(0.018)	(0.010)	(0.010)
EE Rating*Temperature [δ]	-0.032^{**}	-0.037^{***}	-0.037^{***}	-0.038^{**}	-0.032^{***}	-0.032^{***}
	(0.011)	(0.006)	(0.006)	(0.014)	(0.006)	(0.006)
EE Rating*T [μ]	-0.101^{***}	-0.059^{***}	-0.057^{***}	-0.009	0.009	0.008
	(0.030)	(0.012)	(0.012)	(0.030)	(0.014)	(0.014)
EE Rating [β]	0.342^{***}	0.100^{***}	0.099^{***}	0.239^{***}	0.080^{***}	0.081^{***}
	(0.039)	(0.010)	(0.010)	(0.040)	(0.012)	(0.012)
Rainfall		Yes	Yes		Yes	Yes
EE Rating*Rainfall		Yes	Yes		Yes	Yes
Property Characteristics		Yes	Yes		Yes	Yes
Area FE		Yes	Yes		Yes	Yes
Date FE		Yes	Yes		Yes	Yes
Local Market FE			Yes			Yes
EE Rating*Local Market FE			Yes			Yes
RD Bandwidth	3	3	3	3	3	3
R-squared	0.028	0.715	0.715	0.079	0.729	0.729
Observations	2,043,655	2,043,655	2,043,655	1,609,348	1,609,348	1,609,348

Notes: Standard errors in parentheses. * significant at 5%; ** significant at 1% *** significant at 0.1%. Coefficients and standard errors have been multiplied by 100 to interpret them as percentage point increases. Standard errors clustered at the LAD level. The EE Rating ranges from 1 to 100. Temperature is measured in C° and Rainfall in cm. Property Characteristics FE include property type, tenure and number of rooms. Location FE include LAD and urban/rural classification. Date FE include sale year and month. Local Market FE add number of sales per month in the LAD (normalised and demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned). Columns (1) to (3) present the results for the kink at $6.5C^{\circ}$ and columns (4) to (6) for the kink at $17C^{\circ}$. Columns (1) and (4) show the results using Specification (8) which does not include covariates. Columns (2) and (5) use Specification (9) including the vector of baseline covariates. Columns (3) and (6) add controls for local market conditions.

Table B8: RKD results
(Bandwidth of 5)

	6.5C°			17C°		
	(1)	(2)	(3)	(4)	(5)	(6)
EE Rating*Temperature*T [θ]	0.031**	0.039***	0.040***	−0.067***	−0.048***	−0.049***
	(0.011)	(0.006)	(0.006)	(0.018)	(0.009)	(0.009)
EE Rating*Temperature [δ]	−0.022**	−0.028***	−0.030***	−0.016***	−0.016***	−0.017***
	(0.008)	(0.005)	(0.005)	(0.004)	(0.002)	(0.002)
EE Rating*T [μ]	−0.017	−0.007	−0.003	−0.046*	−0.010	−0.009
	(0.020)	(0.011)	(0.011)	(0.022)	(0.011)	(0.011)
EE Rating [β]	0.336***	0.092***	0.090***	0.268***	0.089***	0.089***
	(0.043)	(0.013)	(0.012)	(0.037)	(0.010)	(0.010)
Rainfall		Yes	Yes		Yes	Yes
EE Rating*Rainfall		Yes	Yes		Yes	Yes
Property Characteristics		Yes	Yes		Yes	Yes
Area FE		Yes	Yes		Yes	Yes
Date FE		Yes	Yes		Yes	Yes
Local Market FE			Yes			Yes
EE Rating*Local Market FE			Yes			Yes
RD Bandwidth	5	5	5	5	5	5
R-squared	0.026	0.713	0.713	0.071	0.726	0.726
Observations	2,812,530	2,812,530	2,812,530	2,354,662	2,354,662	2,354,662

Notes: Standard errors in parentheses. * significant at 5%; ** significant at 1% *** significant at 0.1%. Coefficients and standard errors have been multiplied by 100 to interpret them as percentage point increases. Standard errors clustered at the LAD level. The EE Rating ranges from 1 to 100. Temperature is measured in C° and Rainfall in *cm*. Property Characteristics FE include property type, tenure and number of rooms. Location FE include LAD and urban/rural classification. Date FE include sale year and month. Local Market FE add number of sales per month in the LAD (normalised and demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned). Columns (1) to (3) present the results for the kink at 6.5C° and columns (4) to (6) for the kink at 17C°. Columns (1) and (4) show the results using Specification (8) which does not include covariates. Columns (2) and (5) use Specification (9) including the vector of baseline covariates. Columns (3) and (6) add controls for local market conditions.