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The effect of weather on the willingness to pay for residential energy-efficiency

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I study the effects of weather conditions on the economic valuation of energy-efficiency (EE) in the UK housing market. The benefits of EE features depend directly on the expected weather over the ownership time frame (e.g. insulation for maintaining heat during cold periods). However, due to its notorious unpredictability, current weather conditions provide little to no additional information about future weather conditions (beyond common knowledge such as seasonal temperatures). Using transaction-level data of over 5 million residential property sales in England and Wales, I find that weather conditions on 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). I show that these results are unlikely to be driven by energy-cost optimisation or self-selection behaviour. The consistency of the results with intuitive predictions (in the UK the benefits of EE are much higher during rough weather) highlights their importance: People understand the benefits of EE yet make biased intertemporal valuations. I model and discuss psychological biases as the most likely mechanisms and find that salience appears to have the stronger effect. I also present a novel extension to the regression-kink design (RDK) for identifying and estimating the treatment effect when the running variable also moderates the effect of another variable (via interaction). I conclude with policy recommendations. *JEL Codes*: D91, R31, Q41

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1 Introduction

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 an intertemporal problem where, at the time the purchase decision is made, individuals need to estimate all future benefits and costs. While neo-classical economic models typically assume precise utility estimations across time (Rabin 2002*b*), current research suggests that individuals are susceptible to making systematic mistakes when presented with intertemporal problems (see Ericson & Laibson 2019 and DellaVigna 2009 for reviews of the literature). For instance, individuals may be inattentive to information relevant to future utility (salience and limited attention bias – see Gabaix 2019), make overinferences about future states of the world from a small set of recent past observations (overinference bias – e.g. Rabin 2002*a* and Benartzi 2001) or incorrectly project their current preferences into the future (projection bias – see Loewenstein et al. 2003). Recent research provides evidence 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 the 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), a standardised numerical score ranging from 1 (for the least efficient properties) to 100 (for the most efficient). This paper shows 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 over time. If the influence on market valuations of external factors which 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 premia resulting from EE ratings have an important effect on the decision by sellers to invest in EE improvements before marketing their property.

Using data of over 5 millions sale transactions from England and Wales, I 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 mean air temperature was $5C^{\circ}$ in 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 mean air temperature was $20C^{\circ}$.[1] I 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 (£1,460) in 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 price (£5,062). Moreover, I 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. I discuss the importance of these 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.

Importantly, I show that the effects are unlikely to be due to rational optimisation of running fuel costs or self-selection behaviour (of either sellers or buyers). Instead, I propose that the effects are driven by psychological biases. I model and discuss salience (Gabaix 2019), probability overinference (Rabin 2002*a*) and projection bias (Loewenstein et al. 2003) as the most likely mechanisms behind these results. I find evidence suggesting that salience has a stronger effect than

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

probability overinference and projection bias.[2] The results are consistent with the notion that individuals understand qualitatively the benefits of EE, but make imprecise estimations of the magnitude of the utility derived due to the biases described above (Loewenstein et al. 2003). I find that some individuals appear to behave (bounded) rationally and take corrective action in the form of future EE investments once they realise that their utility predictions were inaccurate.

This paper directly contributes to the literature investigating the effects of external factors on intertemporal utility estimations during market transactions. To my knowledge, this paper is the first to provide formal evidence that weather conditions can systematically influence the price paid for energy-efficiency, which by itself is an important finding of increasing relevance due to rapidly changing weather patterns and the constant efforts by governments worldwide to increase energy security (e.g. through retrofitting incentives). Closely related to this paper, Conlin et al. (2007) find that weather conditions over-influence 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 also propose projection bias as one of the mechanisms behind the decisions, and put forward the notion that salience can play a role. This paper shows that weather conditions can also influence decisions in the housing market, where corrective action can be more expensive and difficult once individuals realise their mistakes (e.g. having to replace windows with triple glazing).[3] This paper further contributes to this literature by providing estimates for *pricing* effects attributed to the weather (i.e. how much people are willing to pay for EE under different weather conditions). Busse et al. 2015 include pricing estimations but, due to the structure of the car market they study, only find small and mostly non-statistically-significant effects. In this paper I am able to identify pricing effects reliably because I analyse the population of sale transactions of a fast-clearing market with an auction structure (the hous-

[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 I document.

[3]A working paper version of Busse et al. (2015) also looks at the housing market, although they analyse properties with swimming pools whereas I study EE pricing.

ing market in England and Wales – Section 3 explains the auction structure in detail). I find that salience appears to have a stronger effect than the other psychological biases. This paper adds to the literature on housing EE, Comerford et al. (2021) 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). My results suggest that implementing labelling strategies that include cues and reminders about the different weather conditions can further improve their effectiveness.

This 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). The current RKD literature considers identification and estimation of treatment effects when the slope of the outcome changes when the running variable crosses a threshold (i.e. there is a kink in the effect). I extend this framework to cases where the slope of the outcome *conditional on another independent continuous variable* changes when the running variable crosses a threshold. I derive the additional assumptions required for identification and present a novel non-parametric estimator. The estimated parameter can be interpreted as the change in the strength of the effect from the independent variable when the running variable crosses a threshold (i.e. the change in the effect of the independent variable when moderated by the running variable). I show the applicability of this estimator by documenting the kinked effects of air temperature on EE valuation as explained above. This setup is different from the fuzzy RKD (Card et al. 2015) where the probability of receiving treatment changes (not necessarily from 0 to 1 as in a standard RKD) when a threshold is crossed. In the context of this paper, the probability of receiving treatment changes from 0 to 1 at the threshold (e.g. all sale transactions receive treatment after the $6.5C^{\circ}$ threshold, there is no possible selection given that the running variable is the weather), but the strength of the effect of EE rating on price is different.

The remainder of the paper is organised as follows. Section 2 describes the transaction-level data used in the analysis and the structure of the UK housing market. Section 3 discusses the empirical strategy and presents the results for average-effects estimations. Section 4 details the 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 the results. Finally, Section 6 concludes.

2 Data

I analyse transaction-level data of over 5 million residential property sales in England and Wales from June 2012 to January 2020.[4] The data contains the population of sales between these dates and is constructed by merging records 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. The HMLR data holds records for all sales registered in England and Wales since 1995. The DCLG dataset contains the details of mandatory energy performance certificates (EPC) that must be commissioned before offering a property for sale (Sejas-Portillo et al. 2020).[5] Each transaction contains sale price, sale date, property characteristics, geographic location and the EPC valid at the date of sale. The EPC includes a numerical EE rating score for the property which ranges from 1 (the least efficient) to 100 (the most efficient).[6] Transactions prior to June 2012 are excluded as the legislation in place could be interpreted as requiring sellers to show the EPC to buyers before the sale was complete (i.e. before contracts were signed), but not necessarily before a price was agreed. Policy amendments came into force 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. I also exclude new and repurposed buildings from the analysis because these usually follow a different selling process – namely off-plan – where the sale transaction occurs before construction is complete. An EPC may not be available for these properties when a price is agreed

[4]The data ends in January 2020, before the COVID-19 pandemic disrupted the housing market and the overall economy.

[5]I direct the reader to Sejas-Portillo et al. (2020) for a detailed description of the different datasets and a comprehensive explanation of EPC policies and legislation in the UK.

[6]The EE rating is an energy-cost rating based on engineering calculations and standardised across properties of different types and sizes (Sejas-Portillo et al. 2020).

on, thus the EE rating may not reflect the EE valuation of market participants.[7]

Each sale transaction is matched to monthly air temperature and rainfall data for the geographic region where the property is located (9 regions in England plus Wales).[8] 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 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 the analysis. The slight seasonality of the market is evident in the 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 the 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 sale frequencies at each region suggest different market dynamics and the importance of controlling for geographic area effects in the analysis. Marked differences can also be observed 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-form (e.g. detached) and

[7] 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 this variable is used as a control in the analysis.

[8] The 9 regions in England are the highest tier of sub-national division and are used for a wide range of statistical government and media reports. Their population ranges from approximately 2.5 million (North-East) to 9 million (London). Their population density is mostly homogeneous ranging between 250 and 500 people per km^2 except for London, which as a large urban centre, hosts around 5,700 people per km^2. Wales is one of the constitutive countries of the UK and has a local Government with partially devolved powers. It has a population of approximately 3 million and a density of around 150 people per km^2. A map of the UK with official geographical borders showing the 9 regions in England and Wales is provided in ONS (2019).

produces a standardised EE rating, my analysis controls for these property characteristics 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 (normally 99+ years).[9] Freehold properties sell for higher prices on average. The majority of transactions in the dataset 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, the average EE rating is 60 and the large majority of properties have an EE band of C or D (72.2%).[10] The average sale price in the dataset is £264,398, the average total floor area is $94m^2$ and the average number of rooms is 5.[11] 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
EE Rating (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.

[9] Leaseholders usually pay rent to the owner of the ground.

[10] Sejas-Portillo et al. (2020) provide an in-depth explanation of EE bands and how they are constructed from the EE rating score.

[11] 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 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 Onward	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.

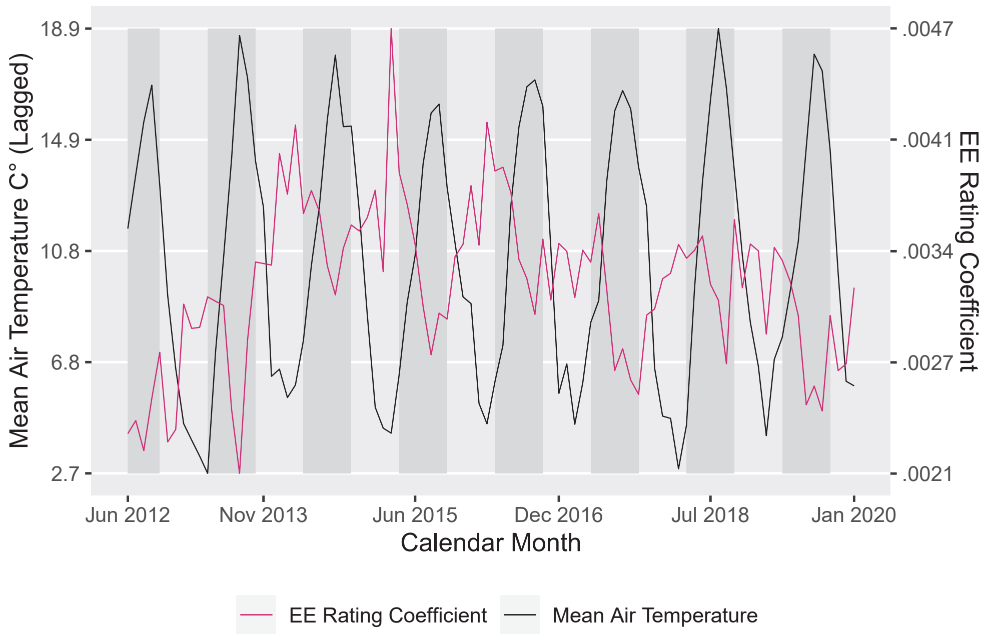
Figure 1 shows the relationship between EE ratings and sale prices across each calendar month, and how it compares to the variation in monthly mean air temperature. The coefficients from regressions of the EE rating on price-per-meter (log) for each calendar month are shown in red,[12] and the monthly mean air temperature in black, 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 completed.[13] A striking pattern is clearly visible: As temperatures rise the relationship between EE rating and sale price becomes weaker, and conversely as temperatures drop the relationship becomes stronger. Sections 3 and 4 provide formal estimations of

[12]Regressions are run separately for each month. Using R^2 instead of the coefficient shows a similar trend.

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

these effects.

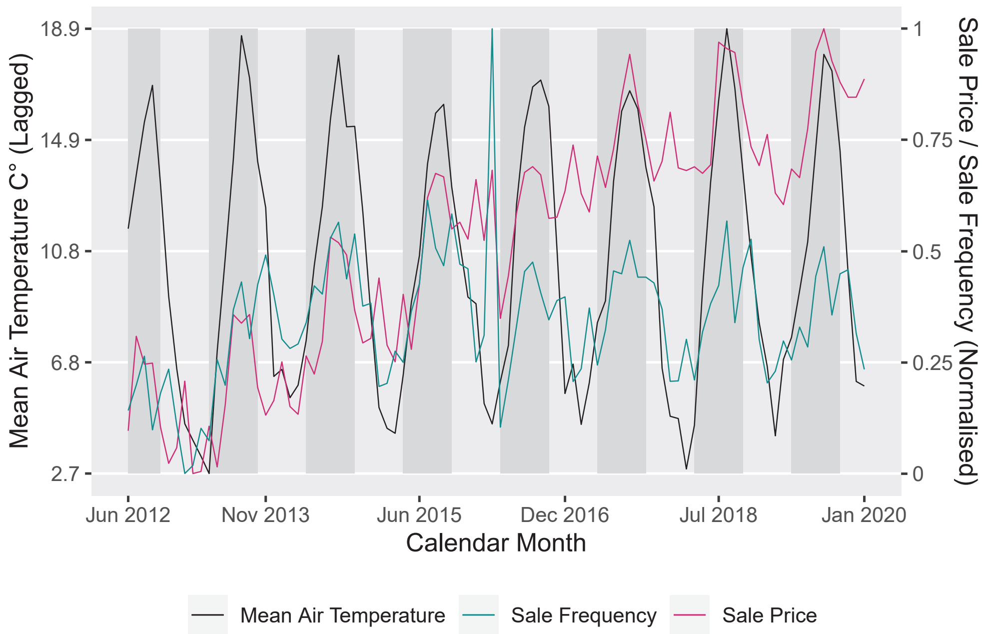
Figure 1: Air temperature - EE rating coefficient on sale price



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 on and the date it is completed. N=5,325,834.

An important concern for the 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, sale frequencies and prices are higher during summer months. Figure 2 illustrates this seasonality by showing monthly averages for the number of transactions and sale prices, and, as before, it includes monthly mean air temperature lagged by one month. The correlation between market activity and air temperature is visible, and thus, it is important for the formal analysis in Sections 3 and 4 to control for local market conditions. I show 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 on and the date it is completed. N=5,325,834.

3 Estimation of weather effects on EE valuation

The 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 the dataset is comprised of 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. I 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 recall that the EE rating, which – as mentioned above – is standardised and ranges from 1 to 100 in discrete 1 unit increments (1, 2, 3 and so forth), 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 discrete EE rating score, allowing me 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 formally sent and accepted, contracts are signed and the ownership transferred. The *sale date* in the dataset records the date when the sale was legally 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, I use the weather conditions of the month before the sale was completed $E[W|t-1]$ in my estimations. I use the previous calendar month to simplify the interpretability of the results from a policy perspective, but my estimates are essentially the same if I use a lagged 30-day rolling average.[14]

The variability of daily mean air temperature within each calendar month is notably low, which provides further evidence that a monthly measure is adequate for my analysis. The average SD of daily mean air temperature within a calendar month in the dataset is $2.46C^{\circ}$, with an average monthly air temperature of $10.17C^{\circ}$, a minimum of $2.52C^{\circ}$ and a maximum of $18.70C^{\circ}$.[15] Rainfall, however, has a much higher variability within each month. The average SD of daily rainfall in a month is $0.42cm$, the average daily rainfall is $0.26cm$, the minimum $0.05cm$ and the maximum $0.53cm$. I test whether monthly rainfall variation influences EE

[14] I also show in Appendix C that my results are robust to alternative lags for weather conditions. The results using a lagged 30-day rolling average are available from the author upon request.

[15] The results for Sections 3 and 4 are virtually the same when aggregating mean air temperature at shorter periods such as weeks (instead of months). Full results are available from the author upon request.

pricing and find that a higher variance leads to a lower effect of rainfall on EE valuations.[16] This suggests that the intensity of rain during short periods can have an important effect on valuations (e.g.individuals looking out the window on a rainy day increasing the salience of EE – Buchheim & Kolaska 2017, Busse et al. 2015). I provide a longer discussion of potential psychological biases behind this finding in Section 5. Importantly, as mentioned earlier, in the data I do not observe the exact day when a buying decision was made. Thus, as with air temperature, I use rainfall aggregated at the monthly level when estimating effect sizes to reduce measurement error and prevent rainfall effects being confounded with approximations of the amount of time that it takes to complete a sale transaction.

I use the weather conditions within the region where the property is located. UK wide weather data is too coarse a measure and would introduce higher measurement error, especially for rainfall. Using regional data follows a more micro approach and offers better, more granular variation.[17] While I cannot observe the previous living or working locations of buyers in the 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

I start with a pooled cross-sectional regression analysis (i.e. all sale transactions are treated as independent[18]) of the relationship between the EE rating, 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 its EE rating. $W_{r,t-1}$ is a vector of weather conditions, namely monthly mean air

[16]Results from the additional regressions are available from the author upon request.

[17]I repeat the analysis using the average air temperature for all of the UK and show in Appendix C that the results hold.

[18]Appendix C shows that the results for the EE rating interacted with weather conditions remain mostly unchanged if I exclude properties that were sold more than once.

temperature and monthly total rainfall, for region r (the region where property i is located) and month $t-1$ (as explained above the month is lagged to account for the time it takes from the moment an offer is made to the date the sale is completed). These variables are centered at their sample mean. Z_i is a vector of control covariates for property characteristics (property type, tenure, property age and number of rooms), location (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 the EE rating on price, and θ, that captures the effect of the interaction term. I interpret the results as the first derivative of equation (2) with respect to EE:

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

As previously explained, the housing market is seasonal with more sales occurring during the summer months. Thus, it is important to rule out that the 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) already partially controls for local market characteristics by including dummy indicators for the sale date (month plus year) and the local authority district (LAD) as the 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 total). To further control for dynamic conditions of the housing market within each LAD, I extend the 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 B. 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). I 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). I 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.[19] 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 $W_{r,t-1}$.[20] Column (3) shows the estimations using Specification (1) and 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 the market controls adequately capture the seasonality of local markets and that the effect of air temperature on property prices is primarily through its relationship with EE (i.e. the interaction terms).

The main coefficients of interest 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. The results can be interpreted using Equation (1a), the first derivative of the specifications with respect to the EE rating. The coefficient θ for the interaction between the EE rating and air temperature indicates that a

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

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

$1C^{\circ}$ increase in mean air temperature (on the month prior to the sale completion) reduces the marginal 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 marginal 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 the intuition for people in the UK. During cold temperatures individuals are more price sensitive towards EE (e.g. heating for comfort) and to energy costs, which translates to a higher valuation of the EE rating. As temperature raises they become less sensitive to these features and costs, and thus the EE rating has a less prominent role in the sale price. Similarly, during rainy periods individuals seem to value EE more and prices are more sensitive to EE ratings. These results are not aligned with fully rational behaviour, I present a more in-depth discussion of their implications in Section 5.

The 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), I find that a 10 points increase in EE rating 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 points increase in EE rating 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 points increase in the EE rating when 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, property age 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 (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 using Specification (1). Column (4) shows the results using Specification (2).

3.2 Property fixed-effects estimation

I also perform the 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 that have more than one sale recorded in the dataset (1,329,057 transactions in total), I estimate property-level fixed-effects regressions with the following specifications:

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

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

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 transactions).[21] An improvement in EE features will normally indicate other improvements were also made to the property. For instance, after installing new insulation, walls can be re-painted and flooring redone, which can increase the sale price of the property irrespective of EE gains. Moreover, sellers who invest in EE improvements may be aiming for overall higher sale returns and thus invest in other improvements such as 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 the 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 the argument, these capture the effects of weather conditions on EE valuation, which, as explained above, is only a portion of the total effect of the EE rating score increase on price. This provides further evidence that weather conditions influence sale prices mainly through features that individuals associate with EE.

Table 4 presents the results from the property fixed-effects analysis. Column (1) shows the coefficients from a regression on price-per-meter (log) of the EE rat-

[21] 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.

ing and the 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 the cross-sectional analysis, the coefficients are remarkably consistent across all specifications and the signs and statistical significance of the estimations confirm the direction of the effects of weather conditions on EE valuation. As discussed above, the coefficient β for EE rating is higher, at 0.459, as it captures other improvements made to the property in addition to EE. The interaction terms θ for EE rating with air temperature (-0.002) and rainfall (-0.001) are nominally smaller than in the 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, property age 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 (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. Column (3) shows the results using Specification (3) and Column (4) using Specification (4).

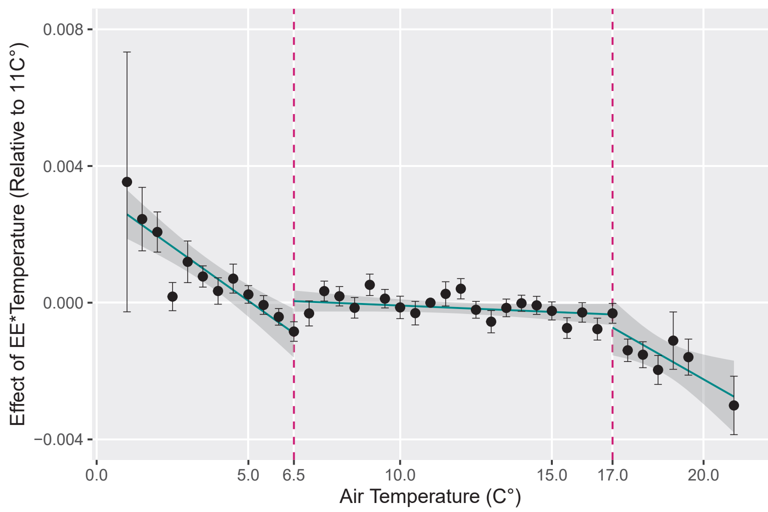
4 Heterogeneity of weather effects

In this section, I study if the uncovered effects are linear or if the effects of severe weather conditions differ from those of mild weather conditions. Figure 3 shows the estimated effect of air temperature on EE valuation across the entire air temperature range (i.e. the coefficient and 95% confidence interval for the interaction term between the EE rating and air temperature $EE_i * W_{r,t-1}$ from Specification 2). I 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 the dataset ($11C^\circ$) is used as the hold-out bin category. The effect on price decreases sharply from $1C^\circ$ to around $6.5C^\circ$, thereafter the relationship stays mostly flat (in relation to the holdout category of $11C^\circ$) up to around $17C^\circ$ where is starts decreasing sharply again. I 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.

I perform the same analysis for rainfall but do not find kinked effects, the relationship appears linear. Figure 4 presents the estimated effect of rainfall on EE valuation across the rainfall range, with $1cm$ bins relative to $0cm$. As before, I use the coefficient and 95% confidence interval of rainfall interacted with the EE rating $EE_i * W_{r,t-1}$ from Specification (2). The effect follows a linear trend, the more it rains the more individuals value EE.

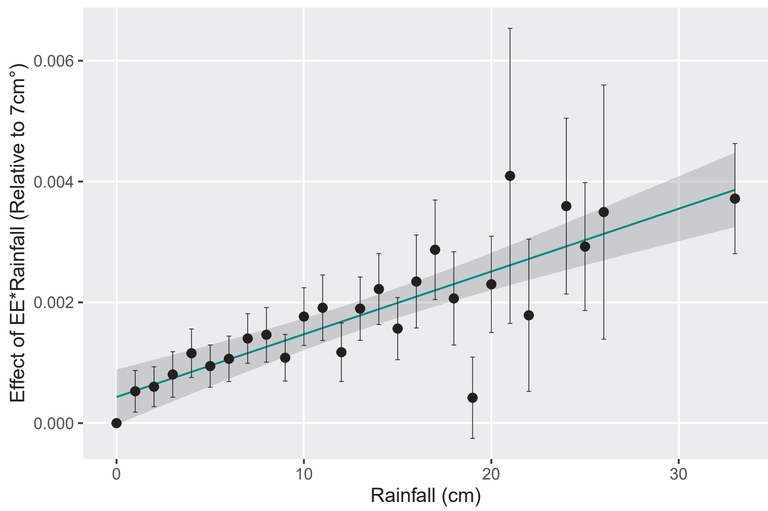
Intuitively, these functional forms are to be expected, individuals are sensitive to very cold temperatures (the kink at $6.5C^\circ$) and to very warm temperatures (the kink at $17C^\circ$), but they are only progressively sensitive to rainfall (e.g. under the perception that once it starts raining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

Figure 3: EE valuation – Air temperature



Notes: This figure plots the coefficients and 95% confidence intervals for the interaction term *EE Rating*Temperature* from Specification (2) across the air temperature range. Sale transactions are grouped in bins of $0.5C^{\circ}$ with $11C^{\circ}$ (the average monthly air temperature) as the holdout category. N=5,325,834.

Figure 4: EE Valuation – Rainfall



Notes: This figure plots the coefficients and 95% confidence intervals for the interaction term *EE Rating*Rainfall* from Specification (2) across the rainfall range. Sale transactions are grouped in bins at $1cm$ intervals with $0cm$ as the holdout category. 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 $17C^{\circ}$, I 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) in the running variable, I extend 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 this setup, the effect of an observable variable EE (energy-efficiency) on the outcome of interest P (price) is moderated by another observable variable W (weather). This effect is captured through the moderation function $f(EE, W)$, which is what the analysis is ultimately interested in. The effect of $f(EE, W)$ on P is heterogeneous across the range of W: If the value of W is over a threshold W_D, then the moderating effect on EE changes. The relationship between $f(EE, W)$ and P will then have a kink at $W = W_D$, and the corresponding change in slope can be estimated using a RKD. This setup is different from the fuzzy RKD (Card et al. 2015) where the probability of receiving treatment changes when a threshold is crossed (not necessarily from 0 to 1 as in a standard RKD). In the setup considered in this paper, the probability of receiving treatment goes from 0 to 1 at the threshold (i.e. all transactions receive treatment after the $6.5C^{\circ}$ threshold, there is no possible selection given that the running variable W is the weather), but the effect of the independent variable EE on outcome P changes through function $f(EE, W)$, which also depends on the running variable W (in other words, the moderating effect of W on EE changes at the threshold).

I first explain the RKD assumptions that must hold for identification of heterogeneous effects using interaction terms. I 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), I assume a random sample of observations where $P \in \mathbb{R}$ represents the outcome of interest and $D \in \{0,1\}$ represents treatment status. The observed outcome is expressed as $P = (1 - D) \cdot P_0 + D \cdot P_1$ where P_0 and P_1 are the potential outcomes with and without treatment respectively. The continuous observable variables $EE \in \mathbb{R}$ and $W \in \mathbb{R}$ have an effect on P. W also determines treatment status (i.e. is the running variable); if W is over a threshold value W_D then treatment is received: $D = \mathbb{1}(W \geq W_D)$. And, specific to this analysis, W also moderates the effect that EE has on P (i.e. W and EE are interacted). I start with the following general specification, which allows for non-separability:

$$\begin{aligned} P &= p(G, U) \\ G &= g(EE, W, D) \\ D &= d(W) \end{aligned} \tag{5}$$

Where $d(.)$ is a deterministic function of W with a kink at W_D. $g(.)$ is a function that captures the independent and interacted effects that W and EE have on P, which as explained above are heterogeneous on D. U represents the error term. The objective is the identification of the change of the moderating effect of W on EE at the kink point W_D, which I denote as the estimand τ. The moderating effect is the cross-derivative of G with respect to D and EE:

$$\tau = \frac{\partial^2 g(ee, w_0, d_0)}{\partial d \partial ee} \qquad \text{where } w_0 = W_D \text{ and } d_0 = d(W_D) \tag{6}$$

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 W on P without interactions. I extend these assumptions for the case where P depends on EE, W and their interaction. All that is required are regularity and smoothness conditions for P, W and EE around the kink threshold: P is assumed to be a continuous function partially differentiable with respect to EE, W and D and cross-partially differentiable with respect to EE and W. Moreover, the partial derivative of D needs to be continuous at threshold W_D. Similarly, the effects of EE, W and their interaction need to be continuous at W_D. Lastly, the conditional density of P given W needs to be continuous at W_D (no sorting into treatment).

In order to estimate τ, $g(.)$ must be continuous and cross-differentiable with respect to EE and W at W_D. This is an additional assumption that is introduced in this 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 (proof in Appendix A):

(7)

$$\tau = \frac{\lim_{w_0 \to W_D^+} \frac{\partial^2 E[P|EE = ee, W = w]}{\partial w \partial ee}\Big|_{w=w_0} - \lim_{w_0 \to W_D^-} \frac{\partial^2 E[P|EE = ee, W = w]}{\partial w \partial ee}\Big|_{w=w_0}}{\lim_{w_0 \to W_D^+} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0} - \lim_{w_0 \to W_D^-} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0}}$$

The numerator of the expression is the change in slope of the effect of the interaction between EE and W on the conditional expectation of P at the kink point $w = W_D$. The denominator is the change in the slope of the deterministic treatment function D at $w = W_D$.

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

4.1.2 Estimation and inference

The RKD identification of interacted effects does not impose any parametric restrictions on $p(.)$. However, some assumptions are required to obtain empirical estimates of τ. Importantly, as shown before, $g(.)$ must be cross-differentiable with respect to EE and W. If $p(.)$ and $g(.)$ are modelled as additive functions, and the interaction between EE and W 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). I employ the following first-order specification:[22]

$$(8) \quad P_i = \alpha + \beta EE_i + \gamma W_i + \delta EE_i \cdot W_i + D_i[\lambda + \mu EE_i + \omega W_i + \theta EE_i \cdot W_i] + \varepsilon_i$$

The coefficients of interest are δ, which captures the slope of the interacted effect of EE and W when treatment is not received, and θ, which captures the additional effect when treatment is received. The coefficients β, γ, μ and ω are necessary to capture the independent additive effects of EE and W on P, however these are not the main focus of the 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)

$$P_i = \alpha + \beta EE_i + \gamma W_i + \delta EE_i \cdot W_i + D_i[\lambda + \mu EE_i + \omega W_i + \theta EE_i \cdot W_i] + \boldsymbol{Z_i}\zeta + \varepsilon_i$$

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 W is exogenous to P, as is the case in the analysis of weather effects, then the denominator term is 1 and the estimator is just θ.

[22] I model EE, W and $EE \cdot W$ as a first order polynomial to simplify interpretation.

4.2 Heterogeneous weather effects on EE valuation

In this section, I apply the identification and estimation strategy presented above to test for the different effects that severe and mild air temperatures have on EE valuation. The outcome of interest is price-per-meter (P), the running variable is air temperature (W) which determines treatment status (D) and also moderates the effect of the EE rating score (EE) on price. Treatment (D) is received if air temperature (W) is above the threshold of interest (W_D), either $6.5C^{\circ}$ or $17C^{\circ}$. Appendix C shows that the variables used in this analysis (air temperature and EE rating) satisfy the identification conditions explained above.

The formal estimates confirm the kinks in EE valuation across monthly mean air temperature that can be observed in Figure 5 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 $6.5C^{\circ}$ threshold and Columns (4) to (6) for the $17C^{\circ}$ threshold. 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 measures 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 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 the RKD specification (coefficients δ and θ) are the ones that capture the changes in the moderating effect of air temperature on EE rating at the thresholds (i.e. the kinked effects of interest).

The estimates for the 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 decision is made is not systematically correlated with any observable property characteristic

Table 5: RKD results

	6.5C°			17C°		
	(1)	(2)	(3)	(4)	(5)	(6)
EE Rating*Temperature*D [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*D [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, property age 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 (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. The estimated coefficients with and without controlling for local market conditions (columns 2 and 3 for the 6.5C° threshold and 5 and 6 for the 17C° threshold) are remarkably stable and similar up to 3 decimal points in many cases. This provides further evidence of the orthogonality of market conditions to the analysis of EE valuation as mentioned above. The full results of the regressions are included in Appendix C and show that the coefficients for weather variables without EE interactions (i.e. the portions not attributable to their moderation of EE) do change when market controls are included.

in a way that would be of concern.

I start by discussing the results for the 17C° threshold using the most restrictive specification (Column 6). When temperature is below 17C°, the coefficient for δ indicates that a 1C° increase in air temperature reduces the marginal effect of the EE rating on price by 0.012 percentage points. However, when air temperature is higher than 17C°, the coefficient for θ shows that an increase of 1C° reduces the marginal effect of EE rating by much more, 0.053 percentage points (in addition to the 0.012 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 marginal 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 marginal effect of air temperature on EE valuation. Appendix C presents and discusses a wide range of robustness checks including continuity tests for EE ratings, density tests (as explained in the previous section) and different bandwidth sizes.

4.2.1 Extreme weather events and heterogeneity across regions

In the previous section, I 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 at the time 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. 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 at the time 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 label this event as 'the beast from the east'. It is worth noting that the analysis in this paper already controls for the date of sale. Nonetheless, to further rule out that the $6.5C^{\circ}$ and $17C^{\circ}$ kink estimations are driven by these extreme events, I run the analysis excluding sales from 2013 and 2018 and show in Appendix C that the results hold. Rather, the results highlight the importance of considering rapidly changing weather conditions in the design of household energy policies.

Similarly, not all regions in England and Wales experience the same weather conditions. 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 a larger proportion of sales occur when air temperature is high. My analysis controls for narrowly defined geographic areas (local authority districts), and their market conditions, to show that the results are not specific to any of these areas. I also show in Appendix C that the results hold even if I remove the regions with the highest proportions of sales under severely cold and warm weather (namely North East and London respectively). The results show that policies aimed at increasing the EE of the housing stock should account for the fact that EE valuations are not homogeneous across the country.

5 Discussion

In this section, I show that the results I document are unlikely to be driven by rational optimisation (namely optimising running fuel costs) or self-selection behaviour. I then proceed to discuss potential psychological mechanisms and biases that can better explain the effects.

5.1 Rational optimisation of running fuel costs

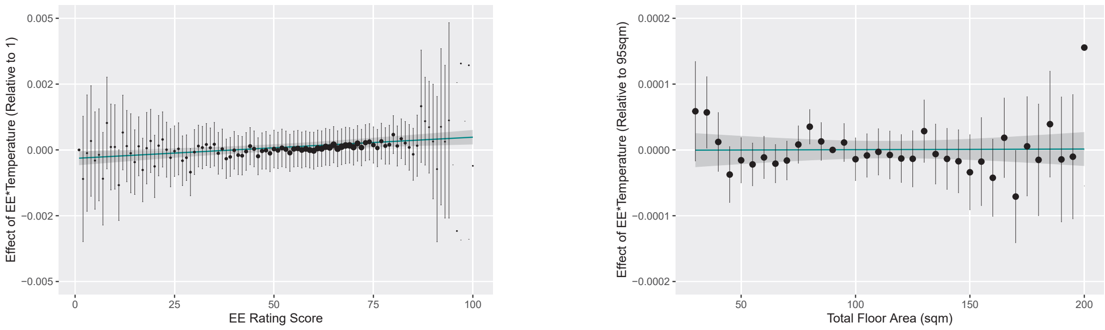
A possible explanation for the results I find would be that individuals are using weather information (either obtained by personal experience or other means like news reports) to optimise their total running energy costs – higher EE translates to lower energy consumption while maintaining the same level of benefits from energy services such as room temperature. If this mechanism was behind the findings then: (a) Current weather should be a good predictor of future weather so that estimating future energy consumption would be possible to a reasonable degree; 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. While climatic seasons (spring, summer, autumn and winter) are pronounced in the UK, the speed at which changes in temperature occur does not follow a set pattern (i.e. the slope of the temperature function in Figure 1 is not predictable). Similarly, the maximum and minimum monthly temperatures for each year are not strongly 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 only be estimated with enough accuracy to be useful up to 10 days in advance (Alley et al. 2019, Bauer et al. 2015). Then, beyond common knowledge which relates to seasonal differences, current weather conditions do not provide much additional information about future weather conditions. Rational individuals, at most, would be able to optimise running energy costs for the present season. Given that in the UK it normally takes over a month before new owners are able to move into a property (as discussed earlier), EE price premia paid during a season (e.g. winter) would predictably only help with the running costs of the next two months. Energy costs would have to be prohibitively high for the price effects I estimate in Sections 3 and 4 to justify the additional expenditure.

Regarding (b), I find that the relationship between air temperature and EE valuation is mostly constant across properties with different EE ratings and sizes. Figure 5 shows the estimated parameter for EE*Air temperature (θ from Specification 2) across the full EE rating scale (Panel a) and across properties of different sizes (Panel b). The effect is mostly constant across both ranges (without statistically significant differences in either case), contrary to the prediction for optimization of energy costs where lower EE or large properties would be expected to produce higher effects.

Neither prediction (a) or (b) holds, therefore the results from Sections 3 and 4 are not indicative of buyers trying to optimise on running energy costs.

Figure 5: EE valuation – Air temperature



(a) Across EE ratings

(b) Across property sizes

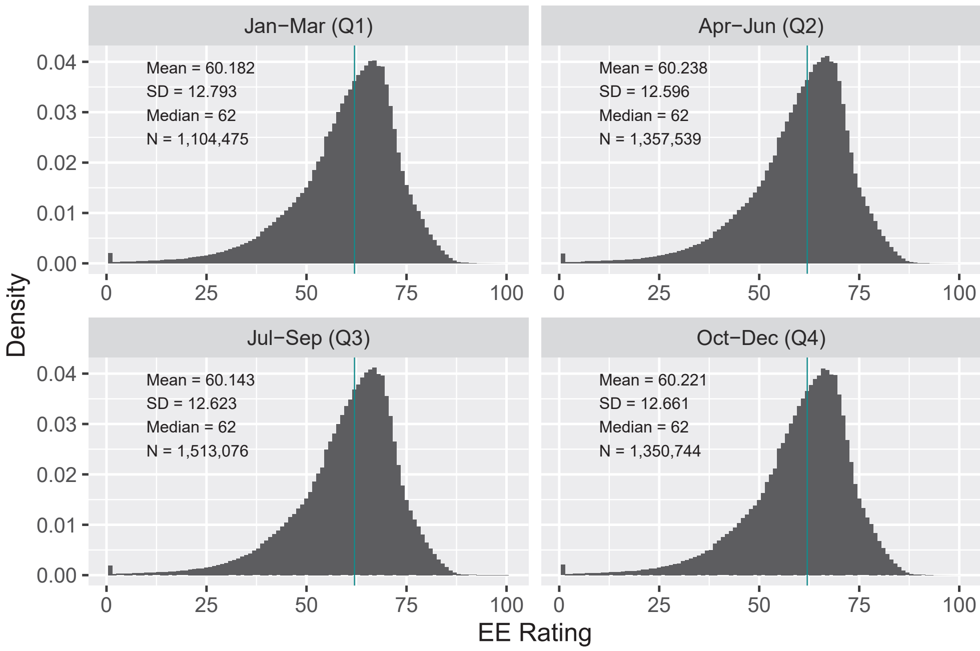
Notes: This figure plots the coefficients and 95% confidence intervals for the interaction term EE*Temperature from Specification 2 across EE ratings and property sizes. Panel (a) shows average effects for each EE rating score using 1 as the hold-out category. Panel (b) shows average effects across property sizes, measured as the total floor area in square-meters (sqm), using 5sqm bins with 95sqm (the average in the data) as the hold-out category. Confidence intervals for bins higher or equal than 95 in Panel (a) and 200sqm in Panel (b) are not drawn since they are disproportionately large due to the small number of properties with these characteristics. N=5,325,834.

5.2 Self-selection behaviour

Another potential explanation that I am able to discard is self-selection behaviour (either strategic or non-strategic). For instance where sellers, with the intention to obtain higher sale prices, make some properties (un)available based on EE ratings and weather conditions (e.g. intentionally delaying the sale of low EE properties until summer). Or where buyers, who are active under different weather conditions, have contrasting EE preferences (i.e. the composition of buyers is different under different weather).

If individuals were successfully self-selecting into the market, then the distribution of sales with respect to EE would be different across weather conditions. It follows immediately for sellers (the supply side), a specific group of properties (e.g. with low EE ratings) would simply not be available to buy during certain periods (e.g. winter). The channel is slightly more subtle for buyers (the demand side), but applicable in this setting. If a large number of buyers – enough to change the composition of demand – with preferences correlated to EE (e.g. environmentally conscientious people preferring high EE) enter the market during specific periods (e.g. winter), then properties with unfavourable ratings (e.g. low EE) will sell comparatively slower (e.g. a flat with lower EE will take longer to sell than a similar flat in the same building with high EE), and, at the very least, a portion of these will sell in the next weather period (while favoured properties will sell soon after they enter the market).

Figure 6: Sale frequency distribution



Notes: This figure plots the distribution of sales with respect to EE conditional on weather quarter. Q1 stands for Quarter 1, Q2 for Quarter 2 and so forth. The vertical line shows the mean EE for each quarter. N=5,325,834.

To test self-selection entry into the market, weather seasons are the most sensible level of time aggregation, it would be unrealistic for individuals to base their decisions to enter the housing market on a shorter time frame. For example, it is not feasible for a seller to go through the process of contracting and dismissing a estate agent, setting up and taking down advertising or transferring mortgages on a weekly or monthly basis. Likewise, it would be difficult for a buyer to negotiate and then cancel a mortgage every month. I am able to observe the true distribution of properties sold in the dataset (as explained in Section 2, I analyse the population of residential sale transactions registered in England and Wales between June 2012 and January 2020). Figure 6 shows that, contrary to the self-selection prediction, the distribution with respect to EE is very similar (almost identical) across weather seasons. I provide formal statistical tests on the equality of the shape of the distributions in Appendix D.

It is also important to note that I fail to find evidence that once in the market, sellers engage in strategic behaviour to obtain higher sale prices. For example, by avoiding viewings during cold and rainy days to make windows without draft-proofing or roofs with leaks less noticeable. If strategic behaviour of this form was successful, then the identified effects would be considerably different between lower and higher EE properties. Continuing with the example, properties with low EE would be 'hidden' during unfavourable weather, making their EE valuation less likely to be influenced by weather conditions. However, I show in Panel (a) of Figure 5 that the weather effects on EE valuation are mostly constant across the EE rating scale (they are not statistically different).

5.3 Psychological mechanisms

I now discuss potential psychological mechanisms that can explain the results I document, specifically salience, probability overinference and projection bias. The results from Sections 3 and 4 are consistent with these three biases, and it is difficult to differentiate them using solely sale transaction data. However, as I explain in more detail below, salience appears to be the main driver of the effect.

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. Within this context, the utility derived at each time period will depend on the weather at the time (i.e. state-dependent utility), since future weather cannot be predicted with certainty, the expected utility for each time period also depends on the (a priori) probabilities of different weather conditions 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 (as a result of consumption smoothing).[23]

Then, from a classic expected utility maximisation perspective (Rabin 2002*b*, DellaVigna 2009), the EE utility valuation (conditional on future weather conditions) of a fully rational individual is given by:

$$U_{ee} = \sum_{t=T_0}^{T_0+T_N} \delta^{t-T_0} \sum_{w_t \in W_t} p(w_t) u(x_t^{ee}|w_t) \tag{10}$$

$$x_t^{ee} = x(c_t^{ee}, f_t)$$

Where U_{ee} is the utility derived from ownership of a property with EE rating ee. Utility is accumulated over all ownership time periods $t \in [T_0, T_0 + T_N]$. Months can be assumed as the unit of t since 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 future weather conditions $w_t \in W_t$ and their probabilities of occurring. The probability that weather w_t occurs is given by $p(w_t)$. The payoff of having a property with an EE rating ee at time t is x_{ee}^t, and the utility derived from payoff x_{ee}^t given weather w_t is $u(x_{ee}^t|w_t)$. The payoff x_{ee}^t represents the cost of maintaining a chosen level comfort (e.g. keeping the property at 'room temperature') and depends on the energy-services consumption c_t^{ee} (provided the property has an EE rating ee) and the cost of fuel f_t at time t.[24] Higher EE increases the payoff by decreasing energy services consumption while maintaining the chosen level comfort.

[23] For simplicity, I will not consider budget constraints or changing preferences, such as lower energy services consumption resulting from environmental concerns. 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.

[24] The model can be extended to account for accumulated EE feature depreciation ee_t^d entering function $f(.)$, but I choose to keep the model simple to help with the discussion of potential mechanisms for EE valuation.

Importantly, when purchasing a property, EE valuation happens at $T_0 - 1$, one 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 of a fully rational individual.

5.3.1 Salience and limited attention

Weather conditions can influence the salience of EE during the purchasing process. Intuitively, while experiencing cold weather, individuals will pay more attention to EE ratings while they search for houses. Current weather will then have a weighting effect on the expected utility derived from EE. Previous research (e.g. Sejas-Portillo et al. 2020, Myers 2019) also shows that limited attention plays an important role in the understanding of energy labels and energy costs in the housing market. The model can be extended to incorporate this effect:

$$U_{ee} = g(\theta, w_{T_0-1}) \sum_{t=T_0}^{T_0+T_N} \delta^{t-T_0} \sum_{w_t \in W_t} p(w_t) u(x_t^{ee} | w_t) \tag{11}$$

Where $g(.)$ can produce values between $[0, 1]$. The parameter θ represents the baseline level of inattention to EE or, equivalently, to the utility derived from EE. If the weather does not influence the salience of EE then $g(.) = \theta$. If weather conditions do influence the salience of EE, then $g(.) \neq \theta$, for example during a very warm summer in the UK $g(.)$ may evaluate to be close to 0.

5.3.2 State-Dependent preferences and projection bias

Individuals may exhibit state-dependent preferences where their utility evaluations depend on the state of the world 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 low. These state dependent preferences could then be projected into the future, thus reducing the expected utility derived from heating services over the whole ownership period and influencing the total EE valuation. This behavioural bias, expecting future preferences to be similar to current ones when contextual factors (e.g. the weather) may be different, is referred to as projection bias in the literature (Loewenstein et al. 2003). An individual exhibiting projection bias would have the following EE valuation function:

$$U_{ee} = \sum_{t=T_0}^{T_0+T_N} \delta^{t-T_0} \sum_{w_t \in W_t} p(w_t)\hat{u}(x_t^{ee}|w_t, w_{T_0-1}) \tag{12}$$

$$\hat{u}(x_t^{ee}|w_t, w_{T_0-1}) = (1-\alpha)u(x_t^{ee}|w_t) + \alpha u(x_t^{ee}|w_{T_0-1})$$

Where the predicted experienced utility function $\hat{u}(.)$ takes into account not only the weather at time t but also the weather 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).

5.3.3 Probability overinference and future weather conditions

It can be seen graphically in Figure 1 that 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 I 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 weeks or months prior to their purchase. In other words, individuals use the weather conditions of the past few weeks or months to make predictions about long term weather trends. The model can be extended to include overinference as follows:

$$U_{ee} = \sum_{t=T_0}^{T_0+T_N} \delta^{t-T_0} \sum_{w_t \in W_t} \hat{p}(w_t | w_{T_0-1}, w_{T_0-2}, ...) u(x_t^{ee} | w_t) \tag{13}$$

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

5.3.4 Identifying the main mechanism

A model that incorporates all of the psychological biases explained above can be written as:

$$U_{ee} = g(\theta, w_{T_0-1}) \sum_{t=T_0}^{T_0+T_N} \delta^{t-T_0} \sum_{w_t \in W_t} \hat{p}(w_t | w_{T_0-1}, w_{T_0-2}, ...) \hat{u}(x_t^{ee} | w_t, w_{T_0-1}) \tag{14}$$

Importantly, if salience plays a prominent role, since $g(.)$ is not compounded or discounted at each time period t, the effect I document will be less sensitive to (or not depend on) the total expected length of the ownership T_N. Moreover, individuals buying a property with the aim to resale it shortly after may be more sensitive to changes in the salience of EE if they expect future buyers to follow a similar valuation process. Conversely, if projection or overinference bias play a larger role, then the effect I identify would increase with the ownership time T_N.

In order to empirically test the relationship between the effect I identify and the total expected length of the ownership T_N, I extend Specification 2 to include dummies for properties that were resold within 2, 5 and 10 years. While I cannot directly observe if the aim of the buyer was to resale the property within this time-frame (or if the sale was circumstantial), I expect that at least some sellers will do this. The dummies that indicate if a property was resold within 2, 5 and 10 years are interacted with the effect I study (namely $EE * Weather$). The dummies are also included without interactions in the regressions. The coefficients for the interactions can be interpreted as the additional marginal effect of weather on EE for properties that were resold within 2, 5 and 10 years.

Table 6: Pooled cross-sectional results with additional effects for properties that were resold within 2, 5 and 10 years

	(1)
EE Rating*Temperature	-0.008^{***}
	(0.001)
EE Rating*Temperature*2-Years	0.001
	(0.001)
EE Rating*Temperature*5-Years	-0.001
	(0.001)
EE Rating*Temperature*10-Years	-0.002
	(0.002)
EE Rating*Rainfall	0.009^{***}
	(0.002)
EE Rating*Rainfall*2-Years	0.008^{***}
	(0.002)
EE Rating*Rainfall*5-Years	0.002^{*}
	(0.001)
EE Rating*Rainfall*10-Years	0.003
	(0.002)
Property Characteristics	Yes
Area FE	Yes
Date FE	Yes
Local Market FE	Yes
EE Rating*Local Market FE	Yes
R-squared	0.723
Observations	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*. The coefficients for *EE Rating*Temperature*2-Years*, *EE Rating*Temperature*5-Years* and *EE Rating*Temperature*10-Years* are for *EE Rating*Temperature* interacted with dummies for properties that were resold within 2, 5 and 10 years. The same applies to the coefficients interacted with *Rainfall*. Property Characteristics FE include property type, tenure, property age 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 (demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned).

Table 6 shows the results of this analysis for the main coefficients of interest (the full results are shown in Appendix E). The additional effect for air temperature on properties resold within 2, 5 and 10 years is not-statistically significant (it is effectively 0), and for rainfall they are positive and significant for properties sold within 2 and 5 years. As explained above, these results support the notion that salience plays larger role than probability overinference and projection bias in the effects I document (since the effect for properties with a larger expected ownership time frame T_N is not bigger in magnitude).

5.3.5 Utility maximisation corrections

If (bounded) rational individuals make incorrect predictions about future utility – whether these are due to salience, overinference, projection bias or another mechanism – they will attempt to take corrective action once they realise their mistake (Conlin et al. 2007). Within the context of my analysis, if individuals purchased a property during a hot summer and mistakenly predicted low future utility from EE features (e.g. they were partially inattentive to the EE rating or projected their current heating preferences), once winter arrives they should realise their misprediction and invest to increase the EE of the property.

While the dataset does not allow me to observe all of the EE investments made to properties (since it is not required to commission a new EPC or energy audit after an improvement but only before selling or renting), I can analyse the subset of properties that were sold more than once and where the EE rating recorded for the resale increased. I run a simple regression on properties that were sold multiple times (1,329,057 observations) where the dependent variable is an indicator of whether the EE rating 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, weather conditions and the interaction term. 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. The estimations in Sections 3 and 4 show that buyers undervalue EE when the weather is warm (i.e. 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

This paper presents evidence that weather conditions, at the time a buying decision is made, can disproportionately influence the economic valuation of EE in the UK housing market. I 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 instance, a 10 points 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) on average if air temperature was $5C^{\circ}$ on the month the buying decision was made. However, the same 10 points 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 points 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), I find 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).

I show that the effects do not seem to be driven by rational optimisation of running fuel costs or by self-selection behaviour. Rather, I argue that the effects are due to psychological biases. I model and discuss salience, probability overinference and projection bias as the most likely mechanisms. I find evidence that suggests salience plays a larger role than probability overinference and projection bias. I also find that some individuals appear to display (bounded) rational behaviour and take corrective action, in the form of future EE investments, once they realise their mistaken (biased) utility predictions.

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 housing markets, 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,[25] thus a low-cost informational intervention where buyers are reminded about winter temperatures and rainfall levels can influence summer purchases (towards a higher valuation of EE) 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 certificates (EPC) shown to potential buyers. I argue against including comparative seasonal cost information in this specific scenario (e.g. including comparisons of energy costs during winter and summer in the EPC), since it could have the drawback of hinting at overpriced energy costs during winter (i.e. buyers 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, as discussed in Section 4.2.1, severe cold weather is more likely in certain regions, thus informational policies can be prioritised in these regions and rolled out as needed to others.

Continuing with this line of research, it is important to further investigate the welfare implications of the results. Specifically, how the effects I document compare to energy prices and EE improvement costs to provide a comprehensive cost-benefit analysis of implementing de-biasing interventions. Also, laboratory experiments can be helpful to further disentangle the effects of salience, overinference and projection bias. Distinguishing between these mechanisms in the field is difficult as they influence decisions in a similar manner (Ericson & Laibson 2019).

[25] Home air conditioning (to keep properties cool) is rare in the UK. In other countries EE may be most beneficial during summer to keep properties cool or similarly beneficial across seasons.

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For Online Publication

All appendices for online publication.

Appendix A RKD interaction estimator proof

Consider the following general specification:

$$P = g(EE, W, d(W)) + u$$

Where, as explained in Section 4, $d(.)$ is a deterministic function of W with a kink at W_D, $g(.)$ is a function that captures the independent and interacted effects that W and EE have on P and u represents the error term. $g(.)$ and $E[u|EE, W]$ must be continuous and cross-differentiable with respect to EE and W at W_D. To simplify notation, g' is defined as the first derivative of g with respect to EE and u'' as the cross derivative of $E[u|EE, W]$ with respect to EE and W:

$$g'(ee, w, d(w)) \equiv \frac{\partial g(ee, w, d(w))}{\partial ee}$$
$$u'' \equiv \frac{\partial^2 E[u|EE = ee, W = w]}{\partial w \partial ee}$$

Then:

$$\frac{\lim\limits_{w_0\to W_D^+} \frac{\partial^2 E[P|EE=ee,W=w]}{\partial w \partial ee}\Big|_{w=w_0} - \lim\limits_{w_0\to W_D^-} \frac{\partial^2 E[P|EE=ee,W=w]}{\partial w \partial ee}\Big|_{w=w_0}}{\lim\limits_{w_0\to W_D^+} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0} - \lim\limits_{w_0\to W_D^-} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0}}$$

$$= \frac{\lim\limits_{w_0\to W_D^+} \left(\frac{\partial g'(ee,w,d(w))}{\partial w} + u''\right)\Big|_{w=w_0} - \lim\limits_{w_0\to W_D^-} \left(\frac{\partial g'(ee,w,d(w))}{\partial w} + u''\right)\Big|_{w=w_0}}{\lim\limits_{w_0\to W_D^+} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0} - \lim\limits_{w_0\to W_D^-} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0}}$$

$$= \frac{\lim\limits_{w_0\to W_D^+} \left(\frac{\partial g'(ee,w,d(w))}{\partial v}\frac{\partial v}{\partial w} + \frac{\partial g'(ee,w,d(w))}{\partial w}\frac{\partial w}{\partial w} + \frac{\partial g'(ee,w,d(w))}{\partial d}\frac{\partial d(w)}{\partial w} + u''\right)\Big|_{w=w_0}}{\lim\limits_{w_0\to W_D^+} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0} - \lim\limits_{w_0\to W_D^-} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0}}$$
$$- \frac{\lim\limits_{w_0\to W_D^-} \left(\frac{\partial g'(ee,w,d(w))}{\partial v}\frac{\partial v}{\partial w} + \frac{\partial g'(ee,w,d(w))}{\partial w}\frac{\partial w}{\partial w} + \frac{\partial g'(ee,w,d(w))}{\partial d}\frac{\partial d(w)}{\partial w} + u''\right)\Big|_{w=w_0}}{\lim\limits_{w_0\to W_D^+} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0} - \lim\limits_{w_0\to W_D^-} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0}}$$

$$= \frac{\lim\limits_{w_0\to W_D^+} \left(\frac{\partial g'(ee,w,d(w))}{\partial w} + \frac{\partial g'(ee,w,d(w))}{\partial d}\frac{\partial d(w)}{\partial w} + u''\right)\Big|_{w=w_0}}{\lim\limits_{w_0\to W_D^+} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0} - \lim\limits_{w_0\to W_D^-} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0}}$$
$$- \frac{\lim\limits_{w_0\to W_D^-} \left(\frac{\partial g'(ee,w,d(w))}{\partial w} + \frac{\partial g'(ee,w,d(w))}{\partial d}\frac{\partial d(w)}{\partial w} + u''\right)\Big|_{w=w_0}}{\lim\limits_{w_0\to W_D^+} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0} - \lim\limits_{w_0\to W_D^-} \frac{\partial d(w)}{\partial w}\Big|_{w=w_0}}$$

$$=\frac{\frac{\partial g'(ee,W_D,d(W_D))}{\partial w}+\left(\frac{\partial g'(ee,W_D,d(W_D))}{\partial d}\lim_{w_0\to W_D^+}\frac{\partial d(w)}{\partial w}\Big|_{w=w_0}\right)+\lim_{w_0\to W_D^+}u''\Big|_{w=w_0}}{\lim_{w_0\to W_D^+}\frac{\partial d(w)}{\partial w}\Big|_{w=w_0}-\lim_{w_0\to W_D^-}\frac{\partial d(w)}{\partial w}\Big|_{w=w_0}}$$

$$-\frac{\frac{\partial g'(ee,W_D,d(W_D))}{\partial w}+\left(\frac{\partial g'(ee,W_D,d(W_D))}{\partial d}\lim_{w_0\to W_D^+}\frac{\partial d(w)}{\partial w}\Big|_{w=w_0}\right)+\lim_{w_0\to W_D^-}u''\Big|_{w=w_0}}{\lim_{w_0\to W_D^+}\frac{\partial d(w)}{\partial w}\Big|_{w=w_0}-\lim_{w_0\to W_D^-}\frac{\partial d(w)}{\partial w}\Big|_{w=w_0}}$$

$$=\frac{\frac{\partial g'(ee,W_D,d(W_D))}{\partial d}\left(\lim_{w_0\to W_D^+}\frac{\partial d(w)}{\partial w}\Big|_{w=w_0}-\lim_{w_0\to W_D^+}\frac{\partial d(w)}{\partial w}\Big|_{w=w_0}\right)}{\lim_{w_0\to W_D^+}\frac{\partial d(w)}{\partial w}\Big|_{w=w_0}-\lim_{w_0\to W_D^-}\frac{\partial d(w)}{\partial w}\Big|_{w=w_0}}$$

$$=\frac{\partial g'(ee,W_D,d(W_D))}{\partial d}$$

Replacing g':

$$=\frac{\partial^2 g(ee,W_D,d(W_D))}{\partial d\partial ee}$$

Appendix B Measures of local market conditions

B.1 Local market sale intensity

The measure of local market sale intensity is computed per local authority district (LAD) per month. It represents the deviation from the LAD average monthly sale frequency. It is computed as:

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

Where $M_{l,t}^{F}$ is the 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 the dataset. And $\sum_{i=1}^{T} F_{l,t_i}$ is the sum of the LAD frequency of sales for all months.

B.2 Local market price intensity

The 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, prices need to be detrended (to remove inflationary effects) and the measure normalised (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).

Prices are first detrended 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 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) denoted as P_i^R.

The price residuals are then demeaned and normalised:

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

Where $M_{l,t}^P$ is the 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 the 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 C Robustness analysis results

Further robustness checks are available from the authors upon request.

C.1 Cross-sectional analysis

Table C1: Effect of UK average air temperature on EE valuation

	(1)	(2)	(3)	(4)
EE Rating	0.119***	0.119***	0.119***	0.119***
	(0.009)	(0.009)	(0.009)	(0.009)
Temperature		−6.153***	−6.147***	−6.557***
		(0.105)	(0.105)	(0.127)
EE Rating*Temperature			−0.004***	−0.004***
			(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 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 $C°$. Property Characteristics FE include property type, tenure, property age 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 C2: Effect of weather conditions on EE valuation
(Excluding properties sold more than once)

	(1)	(2)	(3)	(4)
EE Rating	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 Rating*Temperature			−0.007***	−0.009***
			(0.001)	(0.001)
EE Rating*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 Rating*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, property age 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 C3: Effect of weather conditions on EE valuation
(2-month weather lag)

	(1)	(2)	(3)	(4)
EE Rating	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 Rating*Temperature			−0.008***	−0.008***
			(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, property age 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 C4: Effect of weather conditions on EE valuation
(3-month weather lag)

	(1)	(2)	(3)	(4)
EE Rating	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 Rating*Temperature			−0.006***	−0.007***
			(0.001)	(0.001)
EE Rating*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 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

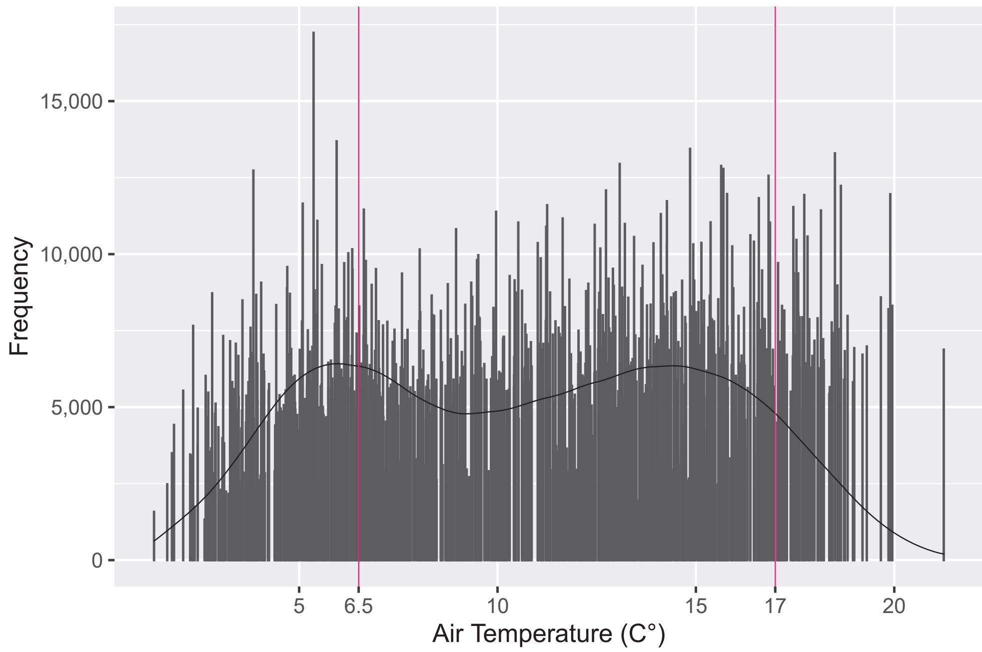
Notes: Standard errors in parentheses. * significant at 5%; ** significant at 1% *** significant at 0.1%. Coefficients and standard errors have been multiplied by 100 to interpret them as percentage point increases. Standard errors clustered at the LAD level. The EE Rating ranges from 1 to 100. Temperature is measured in $C°$ and Rainfall in cm. Property Characteristics FE include property type, tenure, property age 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).

C.2 RKD analysis

C.2.1 Continuity tests

As discussed in Section 4.1.1, an identifying assumption for a valid RKD is that the observed density around the kink point evolves smoothly with respect to the running variable (air temperature in this analysis – Card et al. 2015). A sudden change in the density function would be indicative of self-selection behaviour. In the context of this paper, self-selection seems implausible since either sellers or buyers would have to delay the transaction until the temperature drops below or raises above a given threshold. The data confirms the absence of sudden density changes. Figure C1 shows the frequency distribution of property sales across the air temperature range. Notice that the frequency distribution, although continuous, has mass points because I use monthly regional average temperatures (i.e. the average temperature level is assigned to sales that occurred during a specific month within a specific region). No noticeable changes in the smoothness of the observed density are present around the $6.5C^{\circ}$ and $17C^{\circ}$ thresholds.

Figure C1: Sale frequency distribution - Air temperature

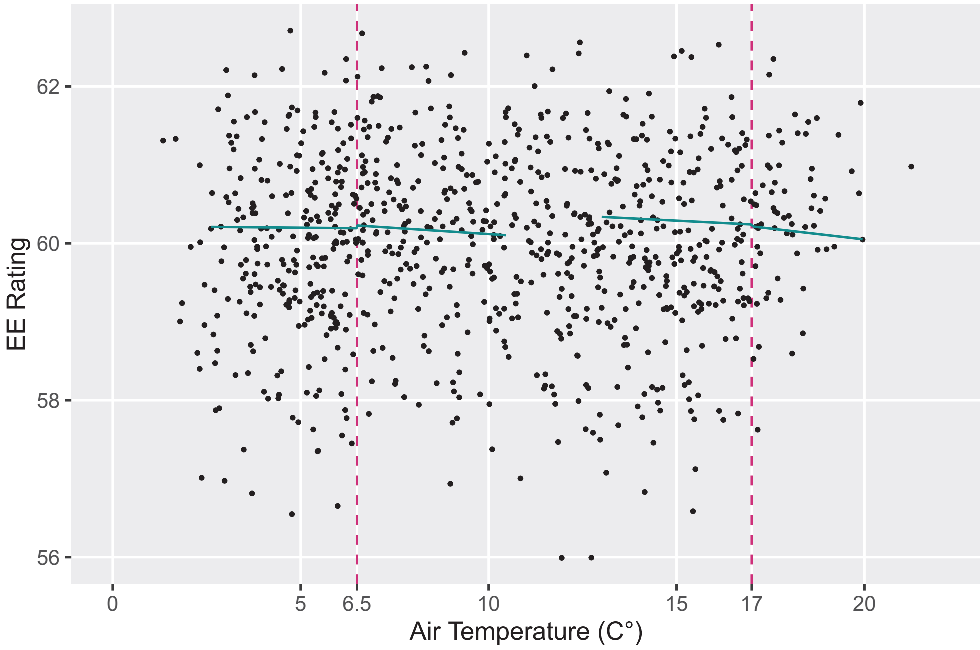


Notes: This figure plots the frequency of sales with respect to air temperature. The solid line shows the kernel density estimation (epanechnikov).
N=5,325,834.

An additional identifying assumption for the RDK extension proposed in this paper, as explained in Section 4.1.1, is the continuity of the independent variable (energy-efficiency) and its first derivative around the kink points in the running variable (air temperature). Importantly, as mentioned previously, the analysis employs regional monthly averages, thus a continuity test of EE needs to control for regional fixed effects and monthly fixed effects, otherwise the estimation would be biased since the air temperature coefficient would capture regional and date effects. It is worth noting that my results of moderated effects do not suffer from these issue as the non-interacted air temperature coefficient would capture these effects keeping the interacted coefficients valid, nonetheless the main results in Section 4.2 show that the coefficients for the interacted terms remain stable with or without the inclusion of any covariates.

Figure C2 shows the average EE of properties across the air temperature range (in $0.001C^{\circ}$ bins). The estimated marginal effect at the means of air temperature after controlling for region and month of sale is also shown. There are no visible changes either in the level or the slope of the effect at the thresholds.

Figure C2: EE - Air temperature



Notes: This figure plots the average EE of sold properties (in bins of $0.001C^{\circ}$) across the air temperature range. The kink points at $6.5C^{\circ}$ and $17C^{\circ}$ are shown with dotted lines. The solid lines show the marginal effects of air temperature before and after the kink points. Marginal effects are constructed from the results of a regression using Specification (15).
N=5,325,834.

I use Specification (15) to formally test the continuity of EE across the air temperature range within a regression-discontinuity design (RDD) framework:

$$EE_i = \alpha + \tau D_i + \beta_{-} W_i + \beta_{+} D_i W_i + \boldsymbol{Z_i} \gamma + \varepsilon_i \tag{15}$$

Where EE_i is the energy-efficiency rating of property i, D_i is a binary variable that determines treatment status (i.e. if a threshold was crossed), W_i is the air temperature measurement, Z_i is a vector of covariates and ε_i the error term. β_{-} and β_{+} are included to test that there is no change in marginal effects (i.e. the derivative) at the threshold, which as mentioned above is important for the RKD analysis.

Table C5 shows the results for the kink points at $6.5C^{\circ}$ and $17C^{\circ}$. The estimates for τ and β_{+} show that the level and first derivative effects on EE do not change at these kink points (i.e. they are close to 0 and without statistical significance at conventional levels), confirming the continuity identifying assumption.

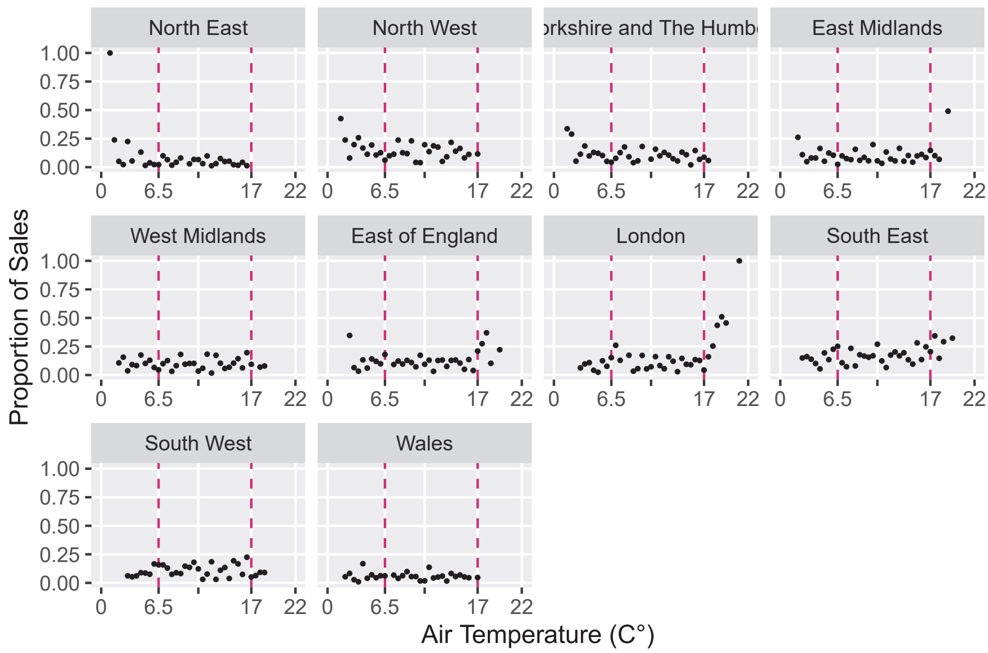
Table C5: RDD results for testing the continuity of EE at the kink points

	$6.5C^{\circ}$		$17C^{\circ}$	
	(1)	(2)	(3)	(4)
D [τ]	0.035	0.035	−0.024	−0.009
	(0.042)	(0.031)	(0.041)	(0.037)
D * Air Temperature [β_{+}]	−0.027	−0.013	−0.032	0.031
	(0.046)	(0.025)	(0.018)	(0.026)
Air Temperature [β_{-}]	−0.004	−0.023	−0.024	−0.078*
	(0.051)	(0.031)	(0.054)	(0.037)
Area FE	Region	LAD	Region	LAD
Date FE	Yes	Yes	Yes	Yes
Property Characteristics		Yes		Yes
Local Market FE		Yes		Yes
RD Bandwidth	4	4	4	4
R-squared	0.006	0.310	0.006	0.313
Observations	2,494,385	2,494,385	1,951,386	1,951,386

Notes: Standard errors in parentheses and clustered at the area level (region or LAD). * significant at 5%; ** significant at 1% *** significant at 0.1%. Columns (1) and (2) present test results for the threshold at $6.5C^{\circ}$ and columns (3) and (4) for the threshold at $17C^{\circ}$. Area FE include Region for Columns (1) and (3) and LAD and urban/rural classification for Columns (2) and (4). Date FE include sale year and month. Property Characteristics FE include property type, tenure, property age and number of rooms. 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).

It is also important to test the continuity in the proportions of sales per region at the kink points. Figure C3 shows the proportions per region across the air temperature range. No discontinuities are visible at the $6.5C^{\circ}$ and $17C^{\circ}$ kink points. Tables C6 and C7 show the formal tests using RDD regressions of the form explained for Specification (15). As before, the estimates for τ and β_{+} show that the levels and first derivatives do not change systematically at the kink points. While the first derivative is statistically significant for London at the $17C^{\circ}$, I show in Table C9 that the RKD results change very little if I remove sales from the London region. RDD estimations for discontinuities at each individual month (i.e. year + month) do not show systematic statistically significant effects either, these results are not included due to their large volume (92 months) but are available from the author upon request. Similarly, RDD tests for the other covariates – property type, tenure, property age, number of rooms, urban/rural classification and local market conditions – do not find systematic discontinuities at the kink points, these results are also available upon request from the author to save space in this Appendix.

Figure C3: Sale proportions per region



Notes: This figure plots sale frequency proportions per region across the air temperature range (in bins of $0.5C°$). The kink points at $6.5C°$ and $17C°$ are shown with dotted lines.
N=5,325,834.

Table C6: RDD results for testing the continuity of proportions per region at the $6.5C^{\circ}$ kink point

	North East	North West	Yorkshire and The Humber	East Midlands	West Midlands	East of England	London	South East	South West	Wales
D [τ]	0.054	−0.037	−0.006	−0.071	−0.067	0.025	0.130	−0.002	0.006	−0.032
	(0.043)	(0.047)	(0.026)	(0.068)	(0.063)	(0.034)	(0.078)	(0.043)	(0.037)	(0.034)
D * Air Temperature [β_+]	0.025	0.007	0.052	0.024	0.023	0.023	0.007	−0.017	−0.101	−0.043
	(0.026)	(0.026)	(0.042)	(0.027)	(0.024)	(0.029)	(0.039)	(0.042)	(0.077)	(0.046)
Air Temperature [β_-]	−0.156	−0.193	−0.160	−0.031	−0.019	0.030	0.185	0.156	0.190	−0.002
	(0.133)	(0.166)	(0.150)	(0.053)	(0.049)	(0.060)	(0.152)	(0.152)	(0.164)	(0.023)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RD Bandwidth	4	4	4	4	4	4	4	4	4	4
R-squared	0.231	0.176	0.121	0.020	0.017	0.025	0.266	0.097	0.115	0.021
Observations	2,494,385	2,494,385	2,494,385	2,494,385	2,494,385	2,494,385	2,494,385	2,494,385	2,494,385	2,494,385

Notes: Standard errors in parentheses and clustered at the region level. * significant at 5%; ** significant at 1% *** significant at 0.1%. Date FE include sale year and month.

Table C7: RDD results for testing the continuity of proportions per region at the $17C^{\circ}$ kink point

	North East	North West	Yorkshire and The Humber	East Midlands	West Midlands	East of England	London	South East	South West	Wales
D [τ]	−0.002	0.044	0.012	0.068	−0.076	0.204	−0.139	0.008	−0.142	0.023
	(0.015)	(0.047)	(0.024)	(0.068)	(0.077)	(0.144)	(0.095)	(0.094)	(0.129)	(0.027)
D * Air Temperature [β_+]	0.055	0.046	0.006	−0.050	−0.015	−0.044	0.118**	−0.084	−0.058	0.027
	(0.049)	(0.043)	(0.022)	(0.051)	(0.022)	(0.045)	(0.030)	(0.073)	(0.057)	(0.028)
Air Temperature [β_-]	−0.081	−0.167	−0.083	−0.008	−0.009	0.060	0.195	0.131	0.035	−0.074
	(0.076)	(0.131)	(0.084)	(0.031)	(0.038)	(0.074)	(0.136)	(0.131)	(0.053)	(0.075)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RD Bandwidth	4	4	4	4	4	4	4	4	4	4
R-squared	0.152	0.249	0.096	0.016	0.026	0.095	0.430	0.089	0.035	0.095
Observations	1,951,386	1,951,386	1,951,386	1,951,386	1,951,386	1,951,386	1,951,386	1,951,386	1,951,386	1,951,386

Notes: Standard errors in parentheses and clustered at the region level. * significant at 5%; ** significant at 1% *** significant at 0.1%. Date FE include sale year and month.

As explained in Section 4.2.1, extreme weather events occurred in 2013, 2018. To show that the effects I identify for air temperatures below $6.5C^{\circ}$ and above $17C^{\circ}$ are not driven solely by these events, I repeat the analysis excluding sales that occurred in these years. Table C8 shows that the estimates remain remarkably stable.

Table C8: RKD results
(Excluding sales from 2013 and 2018)

	$6.5C^{\circ}$			$17C^{\circ}$		
	(1)	(2)	(3)	(4)	(5)	(6)
EE Rating*Temperature*D [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*D [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, property age 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.

Likewise, I discuss in Section 4.2.1 how very low temperatures are more likely in the north of England, and conversely warmer temperatures are more common in the south of England. I show above that the effects at the $6.5C^{\circ}$ and $17C^{\circ}$ kink points are not due to changes in the proportion of sales between regions. As an additional robustness test, Table C9 presents the results of the analysis excluding the regions with the highest proportion of sales under cold and warm weather (i.e. North East for cold weather and London for warm weather). As before, the estimates remain stable.

Table C9: RKD results
(Excluding sales from the North East and London Regions)

	6.5C°			17C°		
	(1)	(2)	(3)	(4)	(5)	(6)
EE Rating*Temperature*D [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*D [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, property age 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.

C.2.2 Empirical specification

Table C10: RKD results
(Bandwidth of 3)

	6.5C°			17C°		
	(1)	(2)	(3)	(4)	(5)	(6)
EE Rating*Temperature*D [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*D [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, property age 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 C11: RKD results
(Bandwidth of 5)

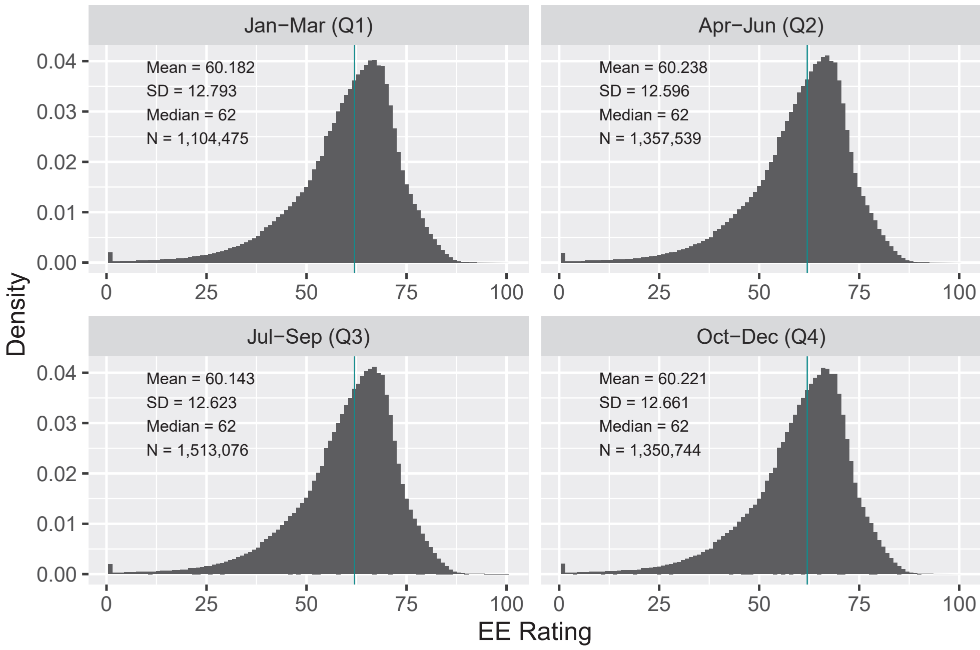
	$6.5C^{\circ}$			$17C^{\circ}$		
	(1)	(2)	(3)	(4)	(5)	(6)
EE Rating*Temperature*D [θ]	0.031**	0.039***	0.040***	−0.067***	−0.048***	−0.049***
	(0.011)	(0.006)	(0.006)	(0.018)	(0.009)	(0.009)
EE Rating*Temperature [δ]	−0.022**	−0.028***	−0.030***	−0.016***	−0.016***	−0.017***
	(0.008)	(0.005)	(0.005)	(0.004)	(0.002)	(0.002)
EE Rating*D [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, property age 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.

Appendix D Distribution of sales across weather seasons

I show in Section 5.2 that the distribution of property sales with respect to EE is very similar across weather seasons. Figure D1 show the density plots.

Figure D1: Sale frequency proportion - Air temperature (by region)



Notes: This figure plots the distribution of sales with respect to EE conditional on weather quarter. Q1 stands for Quarter 1, Q2 for Quarter 2 and so forth. The vertical line shows the mean EE of each quarter.
N=5,325,834.

The distributions are approximately normal but they are skewed (with the mean to the left of the mode). Also, each season sample has a different number of observations (due to the seasonality of the market explained above). Thus, a t-test for comparing the equality of sample means would not be appropriate.

Instead, I apply the non-parametric Wilcoxon rank-sum test (also referred to as the Mann–Whitney two-sample statistic – Wilcoxon 1945, Mann & Whitney 1947) to test for the null hypothesis that two samples are derived from the same population.

Table D1 shows the results of the test for each pair of samples (e.g. Quarter 1 and Quarter 2, Quarter 1 and Quarter 3, and so forth). The p-value shows no statistical differences between Quarters 1, 2 and 4, providing evidence that these samples are taken from the same population. In other words, I find no differences in the proportions of properties with each EE rating sold across these quarters. Regarding Quarter 3, although the p-values suggest statistical significance, the estimated differences and their confidence intervals (measured as the median of the differences – Bauer 1972) are effectively 0 (for instance the estimated median of differences between Quarters 1 and 3 is 0.00000001468347). Also, notice that the number of observations for this quarter is much higher than the others, reducing the accuracy of the test (due substantially different sample sizes – Mann & Whitney 1947). Nonetheless, I repeat the analysis excluding properties sold in Quarter 3 and show in Table D2 that the results remain largely unchanged.

Table D1: Wilcoxon (Mann –Whitney) rank-sum test

Quarters	W statistic	p-value	Difference	CI	N
Q1 and Q2	749,163,368,900.5	0.348	0.000	0.000 | 0.000	1,104,475 | 1,357,539
Q1 and Q3	838,646,771,380.5	0.000	0.000	0.000 | 0.000	1,104,475 | 1,513,076
Q1 and Q4	745,215,953,774.5	0.195	0.000	0.000 | 0.000	1,104,475 | 1,350,744
Q2 and Q3	1,031,547,229,177.0	0.000	0.000	0.000 | 0.000	1,357,539 | 1,513,076
Q2 and Q4	916,590,751,223.5	0.694	0.000	0.000 | 0.000	1,357,539 | 1,350,744
Q3 and Q4	1,017,117,453,597.0	0.000	0.000	0.000 | 0.000	1,513,076 | 1,350,744

Notes: The CI column shows the confidence intervals (lower and upper) of the respective estimated differences. The N column presents the number of observations for the quarter samples separately.

Table D2: Pooled cross-sectional results
(Excluding properties sold in Quarter 3)

	(1)	(2)	(3)	(4)
Energy Efficiency	0.121***	0.121***	0.120***	0.120***
	(0.009)	(0.009)	(0.009)	(0.009)
Temperature		−0.025	0.002	−0.135
		(0.076)	(0.077)	(0.088)
Rainfall		−0.029	−0.025	−0.031
		(0.019)	(0.019)	(0.019)
EE*Temperature			−0.010***	−0.011***
			(0.001)	(0.001)
EE*Rainfall			0.008***	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	0.722	0.722	0.722	0.722
Observations	3,812,758	3,812,758	3,812,758	3,812,758

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, property age 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).

Appendix E Additional effects for properties that were resold within 2, 5 and 10 years

Table E1 shows the results of the analysis including dummies that indicate if a property was resold within 2, 5 and 10 years. The dummies are interacted with the effect I study (namely $EE * Weather$). The coefficients for the interactions can be interpreted as the additional marginal effect of weather on EE for properties that were resold within 2, 5 and 10 years.

Table E1: Pooled cross-sectional results with additional effects for properties that were resold within 2, 5 and 10 years

	(1)
EE Rating	0.087***
	(0.009)
2-Years	−8.948***
	(0.468)
5-Years	−0.182
	(0.156)
10-Years	0.524**
	(0.173)
EE Rating*2-Years	0.304***
	(0.009)
EE Rating*5-Years	0.061***
	(0.006)
EE Rating*10-Years	−0.011
	(0.011)
EE Rating*Temperature	−0.008***
	(0.001)
EE Rating*Temperature*2-Years	0.001
	(0.001)
EE Rating*Temperature*5-Years	−0.001
	(0.001)
EE Rating*Temperature*10-Years	−0.002
	(0.002)
EE Rating*Rainfall	0.009***
	(0.002)
EE Rating*Rainfall*2-Years	0.008***
	(0.002)
EE Rating*Rainfall*5-Years	0.002*
	(0.001)
EE Rating*Rainfall*10-Years	0.003
	(0.002)
Property Characteristics	Yes
Area FE	Yes
Date FE	Yes
Local Market FE	Yes
EE Rating*Local Market FE	Yes
R-squared	0.723
Observations	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. The coefficients for *EE Rating*Temperature*2-Years*, *EE Rating*Temperature*5-Years* and *EE Rating*Temperature*10-Years* are for *EE Rating*Temperature* interacted with dummies for properties that were resold within 2, 5 and 10 years. The same applies to the coefficients interacted with *Rainfall*. Property Characteristics FE include property type, tenure, property age 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 (demeaned) and average sale price per month in the LAD (de-trended, normalised and demeaned).