Green Expectations: Climate Change and Homeowner Valuation of Dwelling Sustainability

Milind Goel†
London Business School, mgoel@london.edu

Abstract

We compile seven million residential property transactions in the United Kingdom and recover discount rates used by homeowners to value dwelling sustainability. To do this, we calibrate present value of energy savings from subsequent improvements in dwelling sustainability to the observed price premium. We find that homeowners accept lower returns for greener dwellings, evidenced by the declining structure of discount rates with increasing dwelling sustainability. Moreover, we exploit the spatial, temporal, tenurial, and vintage variation in premium to demonstrate that homeowners price sustainability following economic principles. Our estimates provide direct measures for rates used to discount climate change mitigation investments.

Keywords: climate finance, discount rates, green premium, energy efficiency
JEL Classification: G11, G50, H43, Q01, Q51, R30

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1 Introduction

Selecting appropriate rates to discount investments in climate change mitigation is challenging because of an absence of observable valuations of economically comparable investments. We address this challenge by recovering discount rates that homeowners use to value dwelling sustainability using a compiled dataset comprising seven million residential real estate sales in the United Kingdom. Improvements in dwelling sustainability are highly correlated with reductions in carbon emissions. The recovered rates, thus, provide direct measures for those used to discount investments in sustainable development, and more broadly, climate change mitigation. We show that homeowners accept lower returns for greener dwellings, evidenced by the declining structure of discount rates with increasing dwelling sustainability. The cross-sectional preference heterogeneity implies that using uniform discount rates is insufficient for optimal policy design and capital appraisal.

To empirically recover the discount rates, we obtain expectations of future energy savings associated with subsequent improvements in dwelling sustainability and equate their present value to the price premium associated with the improvements. We use hedonic regressions to estimate the premium and provide large-scale evidence that dwelling sustainability is priced in the residential real estate market in an economically meaningful manner. For instance, the premium increases in geographies where the energy savings from greener dwellings are higher and decreases in market segments where investments in dwelling sustainability are harder to recoup. The variation in premium illustrates that homeowners price dwelling sustainability following economic principles.

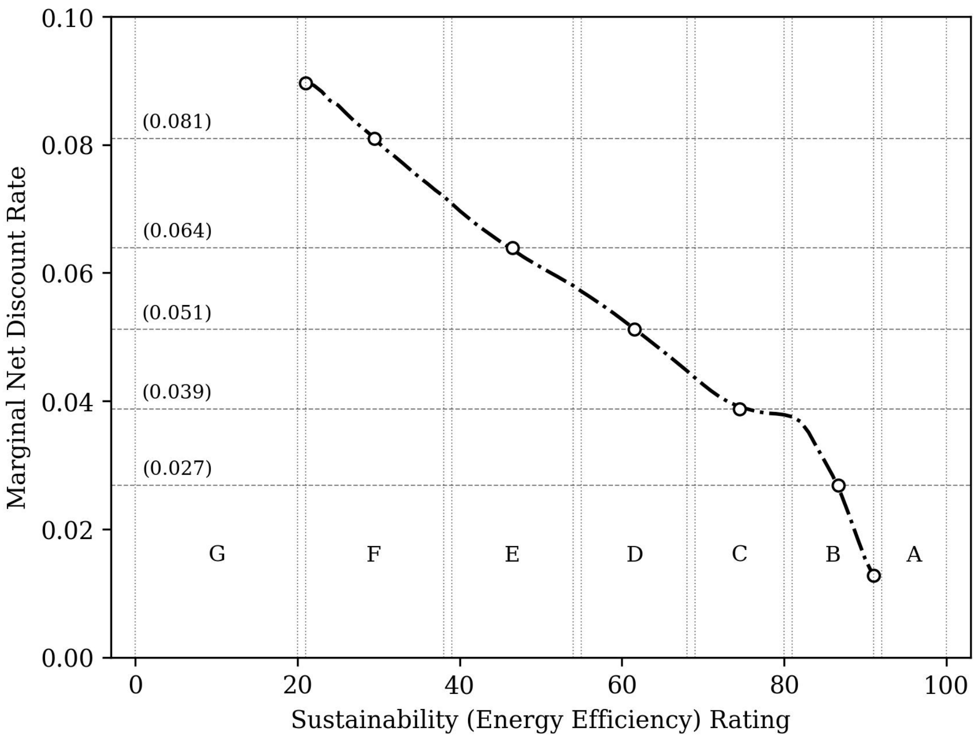
Lastly, we demonstrate that demand for greener dwellings increased following regulatory interventions. The increased demand is not driven by pecuniary incentives. Taken together with the declining structure of discount rates with increasing dwelling sustainability, our findings indicate that homeowners derive non-pecuniary benefits from holding greener dwellings. These non-penuniary benefits become more salient with increasing dwelling sustainability.

Residential real estate is uniquely positioned to address climate risk as both a significant part of the problem and the solution. On one hand, dwellings account for 50% of emissions produced and 70% of energy consumed by the building sector, which adds floor area equal to the surface of the city of Paris each week.[1] On the other hand, the long-duration nature of dwellings exposes them to climate-related risks, which are reflected in their prices (Baldauf, Garlappi, and Yannelis, 2020; Giglio, Maggiori, Rao, Stroebel, and Weber, 2021). Therefore, insights from examining homeowner valuation of dwelling sustainability are informative for appraising investments in climate change mitigation. Moreover, because housing forms the largest component of household portfolios, dwelling prices can be expected to reflect not only a careful evaluation of structural risks and operational costs, but also personal values, such as environmental consciousness.

We exploit the unique regulatory landscape in the United Kingdom, where sustainability ratings of dwellings must be disclosed to prospective buyers and tenants. Dwellings are rated between 1 and 100 following a rigorous inspection by an accredited accessor. We interpret the energy savings from marginal improvements in sustainability ratings as dividends, growing at the same rate as energy prices. Discounting these dividends at a constant rate for dwellings traded under a perpetual ownership covenant enables us to apply the Gordon (1982) growth model for infinitely lived assets. Our approach is motivated by Giglio, Maggiori, and Stroebel (2015, p. 5), who model the prices of dwellings traded under perpetual ownership covenants as the present value of an infinite sequence of rental cash flows. We condition the model on the sustainability ratings of dwellings to measure the *marginal preference* corresponding to each unit rating improvement. This enables us to capture the concavity in marginal energy savings that result from subsequent rating improvements. Then, we recover the marginal net discount rates by computing expected marginal energy savings using our compiled data and calibrating their present value to the premium associated with dwelling sustainability.

[1] The emissions and energy consumption metrics for the building sector are provided by Intergovernmental Panel on Climate Change (2022, Chapter 9). The projected increase in the floor area of the building sector is provided by International Energy Agency (2021, Chapter 3).

Figure 1: Marginal net discount rates



This figure illustrates the marginal net discount rates recovered in Section 5 using a stippled black line. The y-axis corresponds to the rate that homeowners apply to discount energy savings from a marginal improvement in the sustainability rating of a dwelling with an initial rating corresponding to the x-axis. The vertical grid lines mark the thresholds around the alphabetical labels into which the numerical ratings are clustered. The circular markers denote the representative numerical rating for each cluster. The rates corresponding to the markers are illustrated by horizontal grid lines, with the respective values reported in parentheses.

Figure 1 reports the marginal net discount rates obtained from our model using a stippled black line. The y-axis corresponds to the rate that homeowners use to discount energy savings from a marginal improvement in the sustainability rating of a dwelling with an initial rating corresponding to the x-axis. The aggregate marginal discount rate associated with a dwelling rated 40 is 6.97%, decreasing monotonically to 3.79% for a dwelling rated 80. The preference heterogeneity shows that homeowners pay an excess premium for greener dwellings. We term this difference as the *green premium*, which can be interpreted as the utility that homeowners derive from dwelling sustainability. Our central economic insight aligns with the prediction of the equilibrium model of Pástor, Stambaugh, and Taylor (2021) that greener assets should have lower expected returns because investors enjoy holding them and because they hedge climate-related risks.

Applying the unconditional version of the model yields an aggregate net discount rate of 4.43%. The rate is consistent with Groom and Maddison (2019), who calibrate an economic model to obtain short and long run rates of 4.5% and 4.2% for investments in social welfare, such as climate change mitigation. They conclude that the regulator rate of 3.5% does not reflect the societal preferences revealed by private decisions. In contrast, we conclude that, while the regulator rate captures the preferences of high-rated dwelling homeowners, the rate diverges substantially from the preferences of low-rated dwelling homeowners. An important implication of our findings for policymakers is that subsidies based on the regulator rate may not sufficiently incentivise low-rated dwelling homeowners. This cross-sectional variation in discount rates, an order of magnitude higher than the term structure, highlights the economic significance of preference heterogeneity in valuing investments in climate change mitigation.

An empirical recovery of discount rates is naturally contingent on a large-scale and robust measurement of the premium associated with dwelling sustainability, the key barrier to which has been the insufficient volume and veracity of data. We overcome this barrier by designing a custom algorithm that precisely maps the dwelling underlying each trade to its sustainability ratings, energy expenditures, and structural characteristics. The resultant data contains 7.02 million transactions with 5.77 million unique properties, representing one-fifth of all dwellings in England and Wales and 71.6% of the universe of trades over the sample duration. We then aggregate and compile socioeconomic and housing indicators from the national archives, and historical weather records from the meteorological office using geospatial mapping data.

We extensively validate that the properties of the compiled dataset closely correspond to those of the sources. Then, we use a hedonic regression to show that a ten-point increase in dwelling sustainability corresponds to an *energy premium* of 165 basis points, significant at a 1% level. This improvement translates into a reduction in annual emissions by 14 $\mathrm{kgC0_2/m^2}$. To address the concern that unobserved dwelling characteristics may be driving the premium, we show that our estimates remain robust in a homogenised sample of trades with dwellings marked as new. Next, we address potential heterogeneity in the external factors that impact dwelling prices by increasing the granularity of region-specific fixed effects by seven times; the premium persists. We further corroborate our results by validating the economic plausibility of coefficients associated with the hedonic controls and fixed effects. For instance, estimates of period-specific fixed effects closely track the official government property price index.

The variation in energy premium indicates that homeowners price dwelling sustainability following economic principles. First, we show that the premium appreciates in regions where a marginal improvement in dwelling sustainability yields greater energy savings. Therefore, homeowners factor expected energy savings when pricing dwelling sustainability. Using sub-sample analysis, we confirm that the relation between the energy premium and the expected energy savings is approximately linear, which is consistent with our calibration of the present value of energy savings to the estimated premium. Second, we show that the premium and, consecutively, the recovered discount rates, remain persistent over our sample duration. This provides reassurance that our observations are not transient or sensitive to short-run market fluctuations. The persistence of revealed preferences underscores their long-term viability in guiding optimal policy design and capital appraisal.

Third, we show that buy-to-let landlords pay a lower premium than buy-to-live homeowners. Our findings are consistent with the theoretical literature which attributes this disparity to market imperfections preventing landlords from recouping their investments in dwelling sustainability (see Jaffe, Stavins, and Cleveland, 2004; Iwata and Yamaga, 2008; Davis, 2012; Gerarden, Newell, and Stavins, 2017; Cajias, Fuerst, and Bienert, 2019; Berkouwer and Dean, 2022). Furthermore, we deepen this literature by providing large-scale empirical evidence on the differential valuation of sustainability across tenure and by quantifying the magnitude of this effect. Lastly, we demonstrate that homeowners are attentive towards information about dwelling sustainability, evidenced by an attenuation in the energy premium when the issued ratings are older than two years.

Finally, we examine the homeowner decisions to improve their dwelling sustainability. We show that subsequent rating improvements become more costly, which supports our finding that higher-rated dwellings are less likely to have their ratings improved and undergo smaller rating improvements. We then study changes in the likelihood of rating improvements around a regulation that imposed a minimum rating standard on lower-rated rental properties. We find that lower-rated rental properties were more likely to have their ratings improved post-regulation, consistent with Clara, Cocco, Naaraayanan, and Sharma (2024). In addition, however, we show that higher-rated rental properties and lower-rated non-rental dwellings—not required to meet a minimum rating standard—were also more likely to have their ratings improved post-regulation. This finding suggests that the regulation indirectly increased the demand for greener dwellings. Lastly, we confirm that the regulation does not impact energy premium, consistent with the view that it does not affect household energy costs. This finding further underscores the economically meaningful variation in energy premium.

Our work contributes to the active and ongoing debate in the economics of climate change on the appropriate discount rate to be used when valuing investments in sustainability (Stern, 2007; Nordhaus, 2007; Kaplow, Moyer, and Weisbach, 2010; Schneider, Traeger, and Winkler, 2012; Groom and Maddison, 2019). The theoretical foundation of these manuscripts is built on the application and interpretation of Ramsey (1928) rule, which guides the optimal inter-temporal trade-off in climate policy. Giglio, Maggiori, Rao, Stroebel, and Weber (2021) show that real estate prices directly reflect climate risk. They build a tractable asset pricing model that integrates physical climate risk to understand how the term structure of discount rates in residential real estate informs the appropriate choice of rates for climate change abatement. We extend this stream of literature by empirically recovering discount rates through a direct examination of homeowner valuation of economically comparable investments. Our objective is not to develop an economic or asset pricing model, but to examine what a simple valuation framework can tell us about the societal preferences from private decisions. Furthermore, in contrast to extant literature that focuses on the term structure of discount rates, we focus on the previously unexplored cross-sectional preference heterogeneity.

This manuscript is also related to a growing body of literature that models climate risk in property values. Bernstein, Gustafson, and Lewis (2019) show that coastal dwellings exposed to projected sea-level rise sell at an approximately 7% discount relative to otherwise similar dwellings. In contrast, Murfin and Spiegel (2020) find no significant price effects when they match residential real estate transactions with property-elevation and tidal data to compare prices of otherwise similar dwellings but for which the time to inundation will differ depending on the pace of sea-level rise. Baldauf, Garlappi, and Yannelis (2020) show that the dwellings projected to be underwater because of climate change and located in climate change denier neighbourhoods transact at 7% more than those in believer neighbourhoods. We contribute to this body of work by showing that homeowners respond to climate risk and sustainability more broadly, and not only when dwellings are subjected to more immediate disaster risks. This distinction becomes important because disaster risks can influence dwelling prices via channels other than environmental concern, such as changes in the insurance premia or threat of physical destruction.

Lastly, the estimation of energy premium positions this manuscript within the literature that studies whether dwelling sustainability is capitalised in prices (Brounen and Kok, 2011; Cajias and Piazolo, 2013; Fuerst, McAllister, Nanda, and Wyatt, 2016; Jensen, Hansen, and Kragh, 2016). However, the literature widely laments the insufficient volume and veracity of data required to obtain meaningful conclusions (Amecke, 2012; Cerin, Hassel, and Semenova, 2014; Davis, McCord, McCord, and Haran, 2015). For instance, Högberg (2013) emphasises that insights obtained from data sampled from a specific region are not readily generalisable. Therefore, an important contribution of this manuscript is to develop an algorithm mapping dwellings across different data sources. Our compiled data is simultaneously five times larger than the second-largest study (Cajias, Fuerst, and Bienert, 2019) and twice the duration of the second-longest study (Fuerst, Haddad, and Adan, 2020). Although the main focus of our manuscript is the empirical recovery of homeowner preferences, the large-scale examination of previously unexplored spatial, temporal, tenurial, and vintage variation in energy premium extends this stream of work by demonstrating that homeowners price dwelling sustainability following economic principles. The variation in energy premium also explains the divergence in the estimates for energy premium obtained over localised samples used in previous studies.

In contemporaneous work to ours, Clara, Cocco, Naaraayanan, and Sharma (2024) focus on the impact of minimum rating standards on rental properties. They find that lower-rated properties underwent low-cost retrofits to meet the regulatory threshold and that the increase in rental yield does not offset the expenses incurred. In contrast, we study the cross-sectional preference heterogeneity in homeowner valuation of dwelling sustainability. We demonstrate that homeowners derive non-pecuniary benefits from holding greener dwellings. This explains why homeowners bear the excess cost burden to have the ratings of their dwellings improved, even when these dwellings are not subject to regulation.

Our findings have important implications for policymakers and market participants, such as real estate private equity funds, developers, and institutional investors. For policymakers, the preference heterogeneity indicates that tailored interventions like differentiated subsidies and targeted regulations are essential for an effective climate policy. The existence of green premium supports the use of behavioral incentives like mandatory disclosure and awareness campaigns. For investors, understanding the structure of discount rates enables more precise valuation of investments in sustainable development. The economic insights generated from an examination of heterogeneity in energy premium can be leveraged to design localised and market-specific investment strategies, maximising long-term value creation.

The remainder of this manuscript is organised as follows. Section 2 discusses data compilation and sample properties. Section 3 measures the energy premium and Section 4 examines its heterogeneity. Section 5 recovers the discount rates homeowners use to appraise dwelling sustainability. Section 6 examines homeowner decisions to improve dwelling energy efficiency and regulatory impact. Section 7 concludes.

2 Data

We compile official datasets on the energy performance of buildings, price paid for residential property transactions, socio-economic indices, gridded land surface temperature records, and urban classifications, published by various departments of the UK Government to compile a comprehensive dataset that contains 7,022,645 transactions and 5,769,651 unique dwellings. Section 2.1 discusses data construction and Section 2.2 examines sample properties.

2.1 Data construction

We introduce the main sources of data used in the manuscript and how they were compiled in a sequential manner. Technical details are deferred to Section IA.1 of the Internet Appendix.

2.1.1 Transaction values

The Price Paid Data (PPD) is published by HM Land Registry, and provides information about residential property transactions recorded starting January 1, 1995. For each transaction, the database documents the selling price, the date, and select building characteristics such as property type, tenure, and whether the property is new. There are 9,808,400 transactions recorded between January 1, 2010 and December 31, 2020.[2] Our goal is to maximise the number of transactions retained in the final compiled sample.

2.1.2 Energy performance of dwellings

The Energy Performance of Buildings Register is maintained by the Department for Levelling Up, Housing & Communities and publishes data on Energy Performance Certificates (EPC) issued for residential properties starting October 1, 2008, grouped by 341 local authorities (or administrative units) in the United Kingdom.[3] Each EPC provides *current* and *potential* measurements for the energy efficiency, the environmental impact (e.g., carbon emissions),

[2] We restrict our sample between January 1, 2010 and December 31, 2020, because the Energy Performance of Building Register (Section 2.1.2) starts in 2008Q4 and does not contain sufficient data for 2008 and 2009.

[3] We refer to local authorities as districts, regions, or boroughs interchangeably.

and the utility costs (e.g., heating, electricity) of the dwelling for which the EPC was issued. It also records several property characteristics, such as total floor area, built form, proportion of the habitable area glazed, and construction period. The register contains 17,827,487 EPCs for 14,960,081 unique dwellings between January 1, 2010 and December 31, 2020.

In order to investigate the relationship between property values and energy efficiency, and to control for building and transaction characteristics, we must link each transaction recorded in the Price Paid Data with a *valid* EPC. A valid EPC is defined as the most recent certificate for a dwelling issued no earlier than ten years before the transaction date, as per the law. However, there does not exist a unique key or locational identifier that can provide a one-to-one mapping between the two datasets. Therefore, the only method to link the two datasets is through *address matching*.

Unfortunately, addresses are not entered consistently within and between datasets. For example, `FLAT 42, 16A BROADWAY, 413` may also be recorded as `42 BROADWAY, 16A 413`. One method to link addresses is to use approximate matching techniques such as the Levenshtein distance, which computes the minimum number of single-character edits required to change one word into the other. However, such methods suffer from several drawbacks, as illustrated in Section IA.1.1 of the Internet Appendix. Furthermore, given the heterogeneous nature of real estate, inexact matches may distort results substantially. Therefore, we design a custom algorithm that produces *exact* matches, which is detailed in Section IA.1.2 of the Internet Appendix. The trade-off is a smaller dataset post-compilation. We are able to uniquely map 7,239,549 transactions to their EPCs.

We validate and sanitise each feature in the mapped data. Section IA.1.3 of the Internet Appendix documents the implementation details. In particular, Table IA.1 enumerates the features and Table IA.2 summarises the key operations in the order in which they are carried out, with an account of the number of entries lost at each step. The resultant sample contains 7,022,645 transactions.

2.1.3 Upgrade costs

The Energy Performance of Buildings Register also maintains a separate *recommendations* document that complements each EPC. Each document provides a list of energy performance improvements and their expected range of costs – that is, from minimum to maximum – to *upgrade* the property from its current to its potential energy efficiency rating. We extract the cost metrics from each document. For each certificate, we take the average of the suggested range of upgrade costs for each recommended line item. Then, we aggregate these values to obtain a measure of the total upgrade cost associated with that certificate.

2.1.4 Socio-economic indices

The English Indices of Multiple Deprivation (IMD) are published by the Ministry of Housing, Communities & Local Government for the years 2007, 2010, 2015 and 2019. They measure the quality of life experienced by people living in a region. An assortment of indicators covering economic, social, and housing issues are weighted to produce seven component indices – Income, Employment, Health Deprivation, Education, Crime, Housing Barrier, and Living Environment – and an overall composite index for every Lower-layer Super Output Area (LSOA). LSOA are a geographic hierarchy designed to improve the reporting of small-area statistics in the United Kingdom.

There are four considerations in compiling the indices for analysis. First, the format in which these indices are recorded is inconsistent across reports. Second, the LSOA classification used in 2007 and 2010 is different from that used in 2015 and 2019. Third, we must select one of two formats in which the indices are reported: *scores* or *ranks*. Fourth, we must interpolate indices for those years between 2010 and 2020 for which we do not have an IMD report. Section IA.1.4 of the Internet Appendix explains how we address each consideration. We use the Postcode to LSOA 2011 Lookup published by the Office of National Statistics to assign each postcode in our compiled dataset to its corresponding LSOA 2011. We then use LSOA 2011 and transaction year to link IMD to previously compiled data.

2.1.5 Degree days

Heating *degree days* is a measure derived from the historical temperature observations of a region, and is directly proportional to the heating requirements of buildings in that region. To construct degree days, we use temperature averages (TAS) published by the Met Office from 1862 to 2020 derived from a network of land surface observations. The data is available at various frequencies (daily, monthly, annual) and at various resolutions (5×5km, 12×12km, 25×25km). We use monthly TAS recorded over 10,432 5×5km grid points (each represented by a coordinate). Section IA.1.5 of the Internet Appendix documents how year-wise degree days measures for each region are constructed in detail. We use the LSOA 2011 Boundaries database published by the Office of National Statistics to extract representative coordinates for each of the 32,844 LSOA 2011, and assign to them the degree days values for years 2008 through 2021 corresponding to the closest 5×5km grid. As in the case of IMD, we use LSOA 2011 and transaction year to link degree days to previously compiled data.

2.2 Sample properties

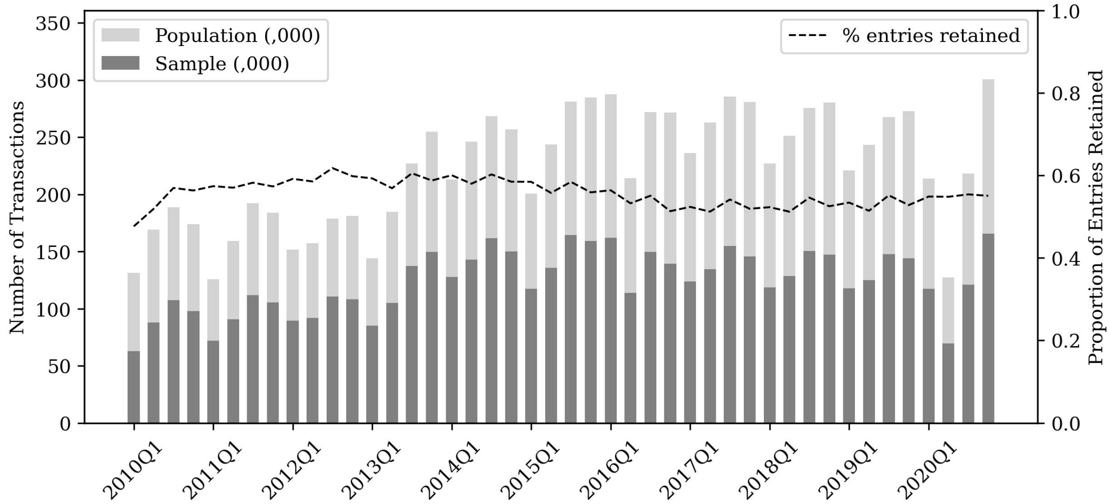
The dataset compiled in Section 2.1 contains 7,022,645 transactions. In Section 3, we remove entries with missing values for any of the included features when estimating the regressions. The resultant *regression sample* contains 5,453,475 transactions.[4] In this section we compare the properties of the regression sample to that of the parent datasets described in Section 2.1. If the properties of our sample closely match with that of the population data, then we can be reassured that our analysis in the subsequent sections is generalisable, and that the estimates obtained from our regressions are representative of the population parameters.[5]

For each quarter, Figure 2 plots the number of transactions retained in the sample against the number of transactions in the Price Paid Data (PPD). We note that the horizontal dashed

[4] This metric corresponds to the full-sample regression in Column (2) of Table 1 in Section 3.2.1.

[5] Though we refer to the parent datasets as the *population data*, it is not strictly true. Properties that may not have had their energy profiles appraised would not be present in the Energy Performance of Buildings Register, as an EPC was not issued. Similarly, Price Paid Data (PPD) may not include transactions that were not registered with the HM Land Registry at the time of a sale.

Figure 2: Transactions sampled each quarter

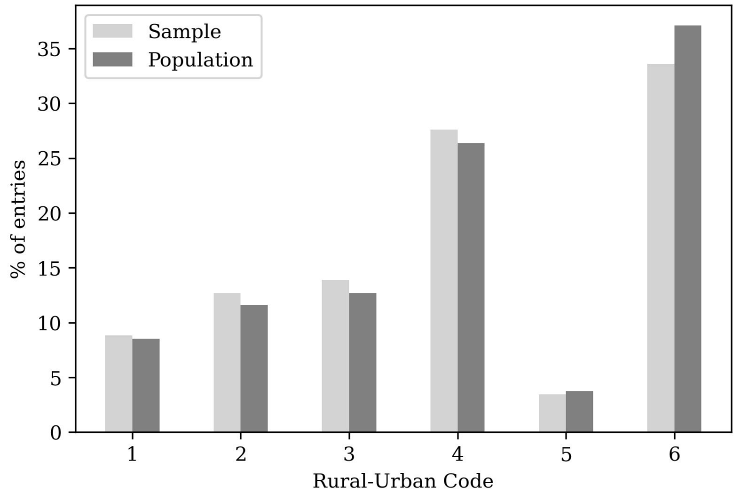


This figure shows proportion of transactions sampled over time. The bars correspond to the primary (left) y-axis, and the horizontal dashed line corresponds to the secondary (right) y-axis. For each quarter, the light grey bars mark the total number of transactions recorded in the Price Paid Data, while the dark grey bars mark the number of transactions retained in the regression sample. The dashed line illustrates the proportion of transactions sampled.

line, which shows the proportion of transactions retained, is stable over the duration of our sample. Figure IA.4 in Section IA.1.6 of the Internet Appendix shows that for each quarter, new dwellings are sampled proportionately from the PPD. Figure 3 shows that dwellings are also sampled proportionally from the PPD across regions with different urban classifications. Additionally, Figure IA.5 in Section IA.1.6 of the Internet Appendix shows that the number of transactions sampled for each local authority is approximately proportional to its population. Finally, the Quantile-Quantile (QQ) plot in Figure 4 charts the quantiles of the degree day measure and the composite multiple deprivation index corresponding to transactions in the PPD (x-axes) against those in our regression sample (y-axes). The circular markers line up along the 45-degree dashed line, indicating that the distribution of measures in our sample and the PPD are nearly identical.

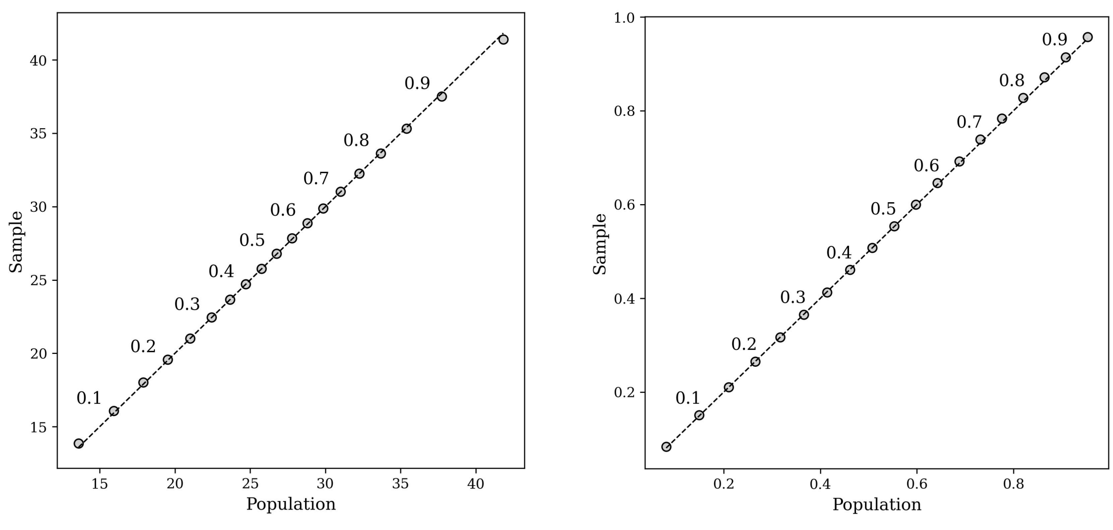
We now compare distributions of some key features of interest. The QQ plot in Panel (a) of Figure 5 plots quantiles of the logarithm of transaction prices in the PPD (x-axis) against those retained in the regression sample (y-axis). The circular markers closely align with the

Figure 3: Distribution of entries by urbanisation



The light grey bars illustrate the proportion of entries present in the regression sample for regions classified into various rural-urban categories. The dark grey bars illustrate a similar breakdown for the Price Paid Data. The rural-urban classifications are published by the Department for Environment, Food & Rural Affairs, and categorise local authority districts in the United Kingdom from most rural (1) to most urban (6).

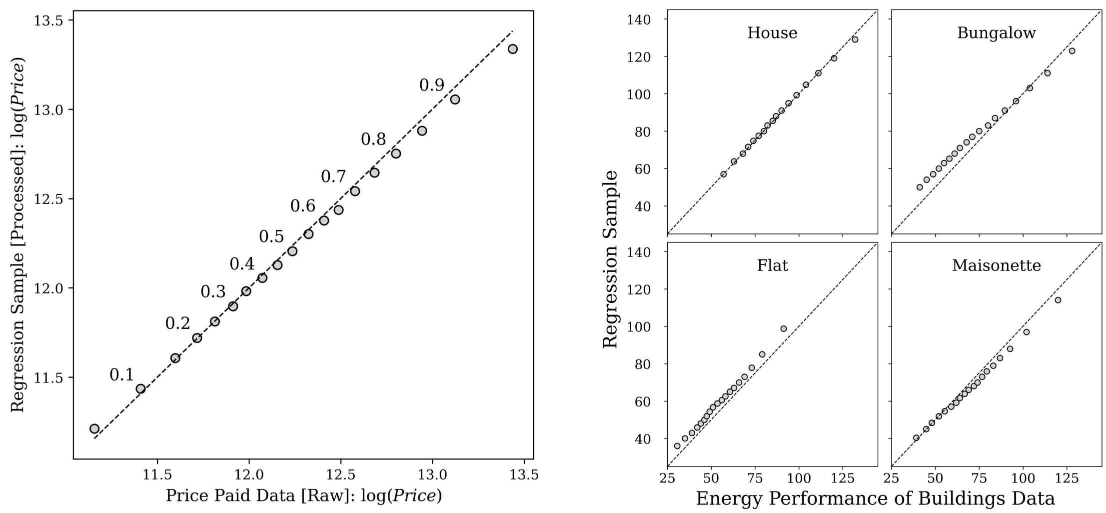
Figure 4: Distribution of environmental controls



(a) Degree days **(b) Multiple deprivation index**

The Quantile-Quantile (QQ) plot in Panel (a) charts quantiles of the degree days measure corresponding to transactions in the Price Paid Data (x-axis) against those in the regression sample (y-axis). Panel (b) replicates the results for the composite multiple deprivation index. The quantiles are represented by the circular markers. The 45-degree dashed line represents a perfect correspondence.

Figure 5: Distribution of features used in the dependent variable



(a) Logarithm of price **(b) Total floor area**

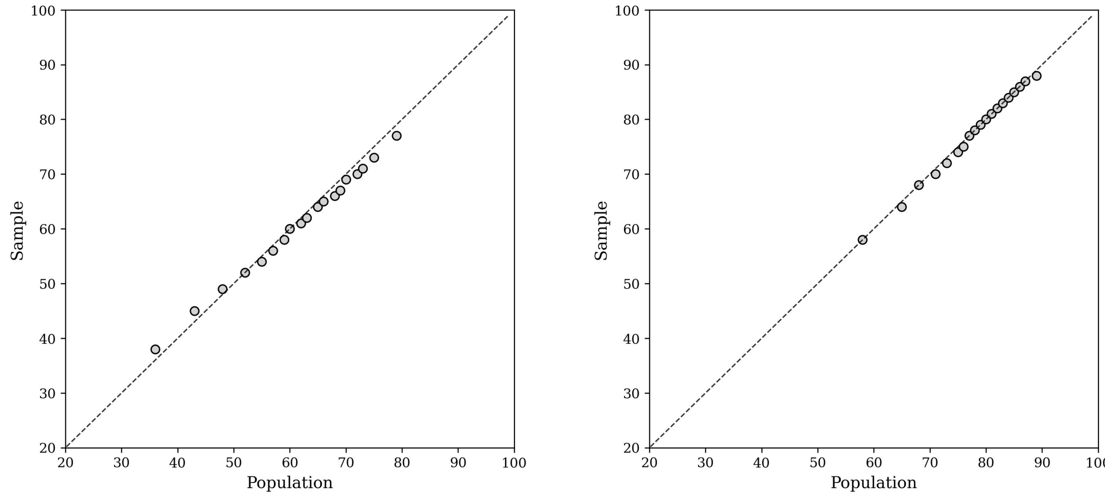
The Quantile-Quantile (QQ) plot in Panel (a) charts quantiles of the logarithm of property prices in the Price Paid Data (x-axis) against those in regression sample (y-axis). Panel (b) shows QQ plots for total floor area for each property type present in the Energy Performance of Buildings Register. The quantiles are represented by the circular markers. The 45-degree dashed line represents a perfect correspondence.

45-degree dashed line, indicating that the distribution of the property prices in our sample is representative of that in the population. The four QQ plots in Panel (b) of Figure 5 chart the quantiles of property sizes (areas) in the Energy Performance of Buildings Register (x-axis) against those retained in the sample (y-axis). Modest deviations from the 45-degree line are expected because we restrict our sample to properties with a total floor area between 20 and 400 squared meters.[6]

Note here that we map the energy certificates for only those properties that correspond to a sale in the HM Land Registry over the duration of our sample. Because the rates at which properties are sold are heterogeneous across different market segments, the composition of tenures (e.g., owner-occupied, private-rental) and property types (e.g., flats, houses) in our

[6] The distribution of total floor area is heterogeneous across property types. For instance, the median size of a flat in the Energy Performance of Buildings Register is $54m^2$ while a house is $88m^2$. Therefore, the size restriction eliminates 1.79% of flats but only 0.05% of houses from the data.

Figure 6: Distribution of energy efficiency ratings



(a) Current ratings **(b) Potential ratings**

The Quantile-Quantile (QQ) plot in Panel (a) charts quantiles of current energy efficiency scores in the Energy Performance of Buildings Register (x-axis) against those in the regression sample (y-axis). Panel (b) replicates the analysis for potential energy efficiency ratings. The quantiles are represented by the circular markers. The 45-degree dashed line represents a perfect correspondence.

sample differs from that of the Energy Performance of Buildings Register.[7] We account for the changes in composition by performing subsample analysis for different market segments (see Section 4.3). Reassuringly, we learn that the properties of our sample match those of the Energy Performance of Buildings Register for all other features enumerated in Table IA.1 in Section IA.1.3 of the Internet Appendix. Panels (a) and (b) of Figure 6 show QQ plots for the numerical current and potential energy efficiency ratings respectively, revealing that the energy profile of the housing stock in our sample represents that of the population dataset. Similarly, Figure IA.6 in Section IA.1.6 of the Internet Appendix illustrates that the composition of the properties belonging to different construction age bands in our sample represents that observed in the Energy Performance of Buildings Register. Finally, Table IA.3

[7] In fact, our *merged sample* produced in Section 2.1 provides a reasonable benchmark for the rate at which properties across different market segments have been sold over time. We also note here that our exact-matching approach (see Section IA.1.2 of the Internet Appendix) slightly undersamples flats and maisonettes because when multiple housing units in the same building omit their SAON, it is not possible to uniquely identify them.

in Section IA.1.6 of the Internet Appendix reports that dwellings with multiple transactions are sampled proportionately from the PPD.

Overall, this section documents that the properties of our regression sample closely match those of the population datasets, reassuring us that the subsequent analyses are generalisable.

3 Measuring energy premium

This section explores whether the energy efficiency of dwellings is priced in the UK residential real estate market. Starting October 01, 2008, it became a legal requirement for homeowners to hold a valid Energy Performance Certificate (EPC) when selling or renting out a property. These certificates are generated using a government-approved software following a thorough inspection and documentation by an accredited assessor. Figure 7 shows a schematic diagram illustrating the lead page of an EPC.[8] Dwellings receive a numerical energy efficiency rating between 1 (*least sustainable*) and 100 (*most sustainable*). The ratings are publicly accessible and must be disclosed on marketplace listings (UK Government, 2007). In general, dwellings with better ratings are expected to expend less energy, exhibit more resilience to climate risks, and increase the utility of homeowners who care about sustainability. Hence, dwellings with higher ratings should command an *energy premium*.

3.1 Methodology

We use hedonic regression models to estimate the energy premium. A hedonic pricing model is a revealed preference method that makes two main assumptions. The first assumption is that the value of a composite object can be decomposed into its constituent components and the external factors that affect the value of that object. The second assumption is that the market values these individual components and factors. These models are widely used in real estate finance to appraise property values, where the market prices are determined jointly by

[8]EPC documents are typically four to six pages long, and include comprehensive information on the energy efficiency of the property, its environmental impact, recommended improvements, and technical details about the property's energy use. The cost of inspection and EPC issuance ranges between £60 and £120.

Figure 7: Schematic diagram of an Energy Performance Certificate

Energy Performance Certificate (EPC)

SAP

17 Any Street, District, Any Town, B5 5XX

Dwelling type:	Detached house	**Reference number:**	0919-9628-8430-2785-5996
Date of assessment:	15 August 2011	**Type of assessment:**	RdSAP, existing dwelling
Date of certificate:	13 March 2012	**Total floor area:**	165 m2

Information about how the energy performance certificate can be used.

Estimated energy costs of dwelling for 3 years	£5,367
Over 3 years you could save	£2,865

Estimated energy costs of this home

	Current costs	Potential costs
Lighting		
Heating		
Hot Water		

Infographic explaining potential future savings

Energy Efficiency Rating

Very energy efficient

	Current	Potential
(92 plus) A		
(81-91) B		82
(69-90) C	72	
(55-68) D		
(39-54) E		
(21-38) F		
(1-20) G		

Less energy efficient

Information about how to interpret the energy efficiency rating or a diagram illustrating its environmental impact

Top actions you can take to save money and make your home more efficient

Recommended measures	Indicative cost	Typical savings	Miscellaneous
1 Recommendation One			
2 Recommendation Two			
3 Recommendation Three			

Contact information and additional notes (for example, about upcoming environmental policies or subsidies)

The schematic diagram illustrates the lead page of an Energy Performance Certificate (EPC). It mirrors the lead page of the sample certificate provided by the UK Government, accessible at https://assets.publishing.service.gov.uk/media/5a748d20ed915d0e8bf19346/1790388.pdf, a copy of which is included in Section IA.2.1 of the Intenet Appendix. The lead page provides identifying information about the dwelling, its current and potential energy efficiency ratings, a breakdown of its utility expenditures, and recommendations for improving the energy profile of the dwelling. The subsequent pages provide additional and more granular information.

the structural characteristics of a dwelling (e.g., floor area, number of habitable rooms, age of property) and the socio-economic and environmental characteristics of the surrounding area (e.g., ambient temperature, proximity to green spaces, quality of schooling, access to transportation hubs). Thus, a hedonic pricing model can be used to determine the extent to which a structural characteristic or an external factor impacts property prices. See Baranzini, Ramirez, Schaerer, and Thalmann (2008) for an overview of hedonic methods in residential real estate markets.

While hedonic models can be general and nonlinear, we assume that the marginal contribution of each constituent component and external factor to the overall property price is linear and additive. This assumption enables us to deploy a linear regression for estimation, which yields several advantages. First, ordinary least squares (OLS) is the standard method of estimating energy premium in the literature, which allows us to directly relate our results to those obtained in prior studies. Second, the statistical properties of the estimates obtained are well understood. Third, augmenting the model with additional covariates, interaction effects, or time-varying components is straightforward. This makes it easier to examine the temporal, spatial, and tenurial heterogeneity in the estimated premium. Furthermore, linear regressions can be naturally extended to difference in differences and regression discontinuity methods that are used in this paper to examine regulatory impact.

Finally, Figure IA.7 in Section IA.2.2 of the Internet Appendix shows that the distribution of the price per unit area is approximately log-normal. Therefore, using its logarithm as the dependent variable helps us assume that the residual follows a conditional normal distribution, in addition to being zero-mean and homoskedastic. Hence, we obtain the most precise unbiased estimates. This allows us to compare our estimates to those obtained from all unbiased estimators, and not only linear ones.

Adapting the notation from Giglio, Maggiori, Rao, Stroebel, and Weber (2021), the unit of observation in our hedonic regression model is transaction $i \in I$ (where $|I|$ is the number of transactions in the sample) of dwelling h, in region r, at time t. The dependent variable in our model is the logarithm of transaction price per unit area of the underlying property, denoted by $\log(P/A)_{ihrt}$. We represent the energy efficiency rating of dwelling h associated with transaction i as S_{ih}, and estimate the following regression specification:

$$\log(P/A)_{ihrt} = \alpha_r + \delta_t + \xi \mathrm{S}_{ih} + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt} + \varepsilon_{ihrt}. \tag{1}$$

The terms α_r and δ_t denote region- and time-specific fixed effects, respectively. We introduce four categories of hedonic controls.[9] Building properties – such as total floor area, dwelling condition, property type, and number of habitable rooms – are denoted by B_h. Transaction characteristics – such as tenure, transaction type, and ownership type – are denoted by T_i. The indices of multiple deprivation are denoted by IMD_{rt}, and control for the quality of the economic, social and housing conditions of region r at time t. We control for the prevailing climatic condition using degree days measure denoted by DD_{rt}, which is directly proportional to the heating requirements of a property in that region. Table 1 enumerates the fixed effects and the hedonic controls included in the analysis.

The parameters associated with the hedonic covariates are represented by θ, γ, ν, and ω, respectively. We are most interested in the estimate of ξ, the parameter associated with energy efficiency rating, which provides a measure for energy premium. Lastly, we denote the residual with ε_{ihrt}.

3.2 Results

This section dicusses the results obtained from estimating Equation (1). Section 3.2.1 reports the results for the energy premium, addresses endogeneity, and performs robustness checks. Section 3.2.2 reports results corresponding to the hedonic covariates and Section 3.2.3 reports those corresponding to the fixed effects. The economic plausibility of estimates corresponding to the hedonic covariates and fixed effects lends credibility to the estimated energy premium.

[9] In a hedonic model, the structural characteristics (B_h and T_i) and external factors (MDI_{rt} and DD_{rt}) are referred to as *hedonic controls*.

3.2.1 Energy premium

Column (1) of Table 1 reports the estimate for energy premium ($\hat{\xi}$) obtained from the baseline regression specified in Equation (1). The regression is estimated over a sample of 5.4 million transactions, the underlying properties of which have an energy efficiency rating between 21 and 91. Standard errors are double-clustered by region and time. The adjusted R-squared is 78.8%. We observe that a marginal increase in the energy efficiency rating of a dwelling is associated with a premium of 16.54 bps (t-statistic = 60.30). The estimate is modest compared to the values implied by previous studies, which range from 19.5 bps (Hyland, Lyons, and Lyons, 2013) to 45 bps (Cajias and Piazolo, 2013).[10] Notwithstanding, the high economic magnitude of observed energy premium raises the concern that $\hat{\xi}$ is capturing the effect of an unobserved variable, such as the quality or the condition of a dwelling at the time of transaction.

If energy efficiency ratings are exogenous, then the expectation of residual ε_{ihrt} conditional on S_{ih} should be zero for all S_{ih}. Figure IA.8 in Appendix IA.2.2 reveals that $\mathbb{E}[\varepsilon_{ihrt}|\mathrm{S}_{ih}] \neq 0$ for properties with energy efficiency ratings less than 21 (label G) or greater than 91 (label A). Therefore, restricting the sample to properties with energy efficiency ratings between 21 and 91 yields an unbiased estimate for energy premium. Indeed, when properties with all ratings are included, we find that the estimate for energy premium reported in Column (2) of Table 1 is biased upwards from 16.54 bps to 19.42 bps.

To further mitigate endogeneity, we homogenise dwelling conditions by estimating Equation (1) exclusively on a sample of 14,267 properties recorded in HM Land Registry as being in a new condition at the time of transaction. Column (3) of Table 1 reports the result. We observe that the energy premium appreciates to 31.21 bps. This suggests that retrofit value is not driving the premium and that homeowners purchasing new dwellings are perhaps more attentive to the energy performance of their dwellings. The latter interpretation is supported

[10] Hyland, Lyons, and Lyons (2013) report a 1.3% premium for each unit improvement on a 15-point scale. We multiply 1.3% by 15 and then divide by 100 to arrive at a 19.5 bps estimate. Cajias and Piazolo (2013) report a 45 bps premium for each 1% improvement in dwelling energy efficiency.

Table 1: Estimates for energy premium

	(1) Baseline Regression	(2) Including Labels AG	(3) New Condition	(4) Excluding London	(5) Outcode Fixed Effect
Energy Rating	0.1654***	0.1942***	0.3121***	0.1683***	0.1510***
	(0.003)	(0.003)	(0.044)	(0.003)	(0.002)
(*Fixed Effects*)					
Local Authority	Yes	Yes	Yes	Yes	No
Time (Year)	Yes	Yes	Yes	Yes	Yes
Outcode	No	No	No	No	Yes
(*Structural Controls*)					
Total Floor Area	Yes	Yes	Yes	Yes	Yes
Property Type	Yes	Yes	Yes	Yes	Yes
Built Form	Yes	Yes	Yes	Yes	Yes
Habitable Rooms	Yes	Yes	Yes	Yes	Yes
New Condition	Yes	Yes	No	Yes	Yes
Construction Band	Yes	Yes	Yes	Yes	Yes
Glazed Area	Yes	Yes	Yes	Yes	Yes
Multi-Glaze Proportion	Yes	Yes	Yes	Yes	Yes
(*Transaction Controls*)					
Tenure	Yes	Yes	Yes	Yes	Yes
Transaction Type	Yes	Yes	Yes	Yes	Yes
Ownership	Yes	Yes	Yes	Yes	Yes
(*Climatic Control*)					
Degree Days	Yes	Yes	Yes	Yes	Yes
(*Deprivation Indices*)					
Income	Yes	Yes	Yes	Yes	Yes
Employment	Yes	Yes	Yes	Yes	Yes
Health Deprivation	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes
Crime	Yes	Yes	Yes	Yes	Yes
Housing Barrier	Yes	Yes	Yes	Yes	Yes
Living Environment	Yes	Yes	Yes	Yes	Yes
Observations	5,400,384	5,453,475	14,267	4,721,908	5,400,433
Adjusted R^2	0.7876	0.7871	0.7465	0.7421	0.8153

This table reports estimates of energy premium obtained from regression specified in Equation (1). Column (1) limits the sample to dwellings with energy efficiency ratings between 21 and 91, while Column (2) expands the sample to include dwellings with ratings below 21 or above 91. Column (3) focuses on dwellings recorded by HM Land Registry as being in new condition. Column (4) excludes the 33 boroughs within the Greater London area. Column (5) replaces borough-level fixed effects with outcode-level fixed effects. The dependent variable is the logarithm of price per unit area. The estimates are multiplied by 100 and should be read as percentages. Standard errors are reported in parentheses and are double-clustered by region and time. Lastly, p-values less than 0.10, 0.05, and 0.01 are demarcated by one (*), two (**), and three (***) stars, respectively.

by the findings in Section 4.4. Moreover, Section 6.1 shows that the median cost, expressed as a proportion of dwelling price, associated with a unit improvement in the energy efficiency rating of a dwelling is 42 bps. Therefore, if anything, the observed premium is too low.

We perform several additional robustness checks. Column (4) of Table 1 shows excluding the 33 boroughs of the Greater London area has a negligible impact on the observed premium. This provides reassurance that the demand inelasticity and high density of housing in London are not confounding the results. A refined vignette is provided by Table IA.8 in Section IA.3 of the Internet Appendix, which shows that the premium persists across subsamples of regions based on the various levels of urbanisation defined by the Department for Environment, Food & Rural Affairs. Next, we re-estimate Equation (1) with outcode-level fixed effects and report the results in Column (5) of Table 1. We observe that the premium depreciates to 15.10 bps. Outcodes represent a much more granular geographic classification within which the energy performance of dwellings is expected to be more homogenous. Hence, a modest depreciation in the observed premium is unsurprising as the fixed effects will absorb variations specific to these finer geographic divisions.

Finally, subsequent sections demonstrate that estimates of the coefficients associated with the fixed effects and the hedonic controls are quantitatively justified. We further observe that the premium is not only persistent over the duration of our sample but is also heterogeneous in an economically meaningful manner. Section IA.2.3 of the Internet Appendix also shows that our conclusions are robust to potential discontinuities around different labels or groups into which energy efficiency ratings are categorised. These findings lend additional credibility to the observed energy premium.

3.2.2 Hedonic controls

Table 2 reports the estimates of parameters associated with select hedonic controls included in Equation (1). It is reassuring to observe that the estimates are plausible from an economic standpoint. For instance, a 10m^2 increase in the floor area is associated with a 2.8% decline in the price per unit area, which indicates economies of scale. Similarly, properties in a new

Table 2: Hedonic regression estimates for select independent variables

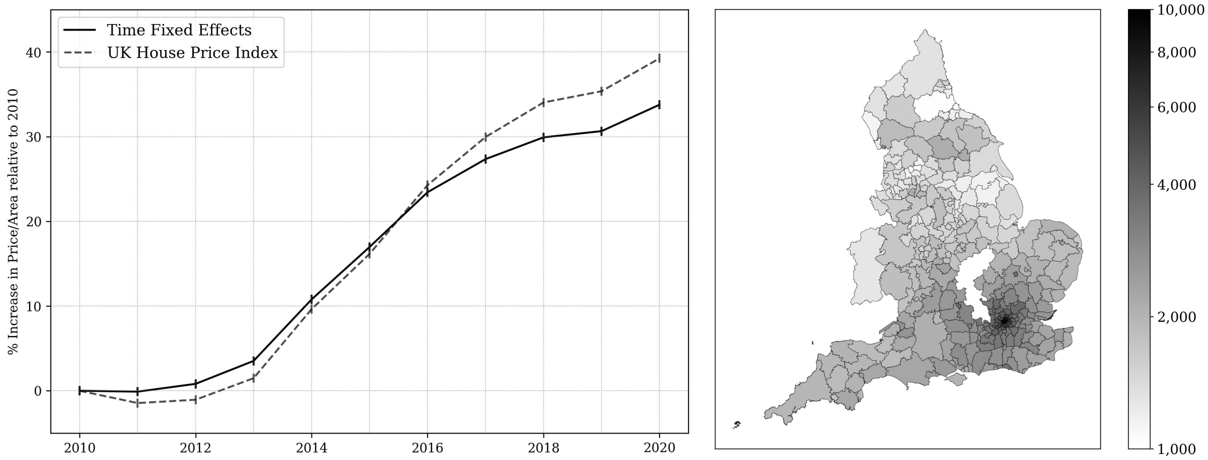
Energy Rating	0.1654***	(0.003)			
(*Property Type*)			Total Floor Area	-0.2768***	(0.002)
Maissonette	*Omitted*		Habitable Rooms	1.8725***	(0.046)
Flat	1.9054***	(0.179)			
House	9.7657***	(0.356)	(*Ownership*)		
Bungalow	24.3535***	(0.730)	Freehold	6.2906***	(0.332)
			Leasehold	*Omitted*	
(*Construction Band*)					
1900 pior	7.9430***	(0.188)	(*Tenure*)		
1900-1929	*Omitted*		Social Rental	*Omitted*	
1930-1949	3.2282***	(0.208)	Private Rental	8.3240***	(0.336)
1950-1966	1.6009***	(0.208)	Owner Occupied	13.8544***	(0.375)
1967-1975	1.6389***	(0.242)			
1976-1982	4.2634***	(0.248)	Degree Days	-0.0844**	(0.036)
1983-1990	7.9269***	(0.259)			
1991-1995	10.6504***	(0.285)	(*Deprivation Indices*)		
1996-2002	11.6236***	(0.285)	Income	17.1983***	(0.854)
2003-2006	10.5750***	(0.338)	Employment	0.8910	(0.908)
2007 onwards	10.2033***	(0.366)	Health Deprivation	-4.8404***	(0.853)
			Education	43.0583***	(0.572)
(*New Condition*)			Crime	5.8186***	(0.365)
No	*Omitted*		Housing Barrier	-2.5547***	(0.252)
Yes	3.4599***	(0.773)	Living Environment	-1.6334***	(0.402)
Observations	5,400,435		Adjusted R^2	0.7876	

This table reports the estimates obtained from Equation (1) for selected independent variables. Other covariates include region fixed effects, time fixed effects, built form, glazing characteristics, and transaction type. The dependent variable is the logarithm of price per unit area. The estimates are multiplied by 100 and should be read as percentages. The standard errors are two-way clustered by region and time. The associated *p*-values are reported in parentheses; values less than 0.10, 0.05, and 0.01 are demarcated by one (*), two (**), and three (***) stars, respectively.

condition sell at a premium of 3.46%. Dwellings purchased with the intention of occupation transact at a 5.26% premium relative to those with an intention of leasing out. We observe that the value of a dwelling declines with age, except for those constructed before the 20^{th}-century, which transact at higher prices. Indeed, period properties command higher market valuations owing to their unique character and history. Unsurprisingly, bungalows (+22.44%) and houses (+7.86%) are more expensive than flats, and a covenant for perpetual ownership, known as a freehold, is more valuable (+6.29%).

Turning our attention towards location-based covariates, we observe that property values decline by 0.08% for each unit increase in the degree days measure. One potential explanation is a higher demand for housing in more temperate regions. However, the effect is economically

Figure 8: Fixed effects obtained from baseline regressions



(a) Time **(b) Region**

Panel (a) illustrates the appreciation in property prices relative to 2010. The solid line shows the price growth implied by the estimates of the time fixed effects obtained from Equation (1). The dashed line shows the price growth implied by the property price index published by HM Land Registry, accessible at https://landregistry.data.gov.uk/app/ukhpi. Panel (b) illustrates relative property prices implied by the region fixed effects obtained from Equation (1) through a heatmap. Prices are benchmarked to a dwelling which costs £10,000/m^2 in Kensington and Chelsea, the most expensive borough in the United Kingdom. The values reported in the legend are spaced in accordance with the logarithmic colour scale used in the heatmap.

small. A higher deprivation index value indicates lower deprivation. Thus, large and positive estimates corresponding to income, education, and crime indices suggest that more affluent neighbourhoods command a substantial premium. The employment index does not predict property prices.[11] Counterintuitively, the estimate corresponding to the health deprivation index is negative. Affluent neighbourhoods are expected to have better access to healthcare. Hence, a likely reason is that a higher number of cases are reported.[12] The negative coefficient corresponding to the living environment index indicates poorer air quality and higher road accidents in more congested (but expensive) areas. The negative estimate corresponding to the housing barrier index is unsurprising because a higher value indicates more affordability.

[11] The effect of the employment index on property prices is likely absorbed by income and education indices. In addition, regions with higher income but otherwise similar employment rates are likely more expensive.

[12] The health deprivation index is not based on access to healthcare, but rather, derived from statistics on mortality, morbidity, disabilities, and mood or anxiety disorders. An alternative explanation could be that the population in inexpensive neighbourhoods is younger, and therefore, healthier.

3.2.3 Fixed effects

Panel (a) of Figure 8 tracks the evolution of property prices over the duration of our sample, relative to 2010. The solid black line tracks price growth implied by the time fixed effects in the baseline regression, whereas the dashed line tracks the price growth implied by the price index published by HM Land Registry. We observe that the former closely tracks the latter. For each local authority, Panel (b) of Figure 8 illustrates the relative price of a dwelling that costs £10,000/m^2 in Kensington and Chelsea, the most expensive local authority in the UK. As expected, regions farther from London are more affordable. Overall, estimates for region and time fixed effects are realistic from an economic standpoint.

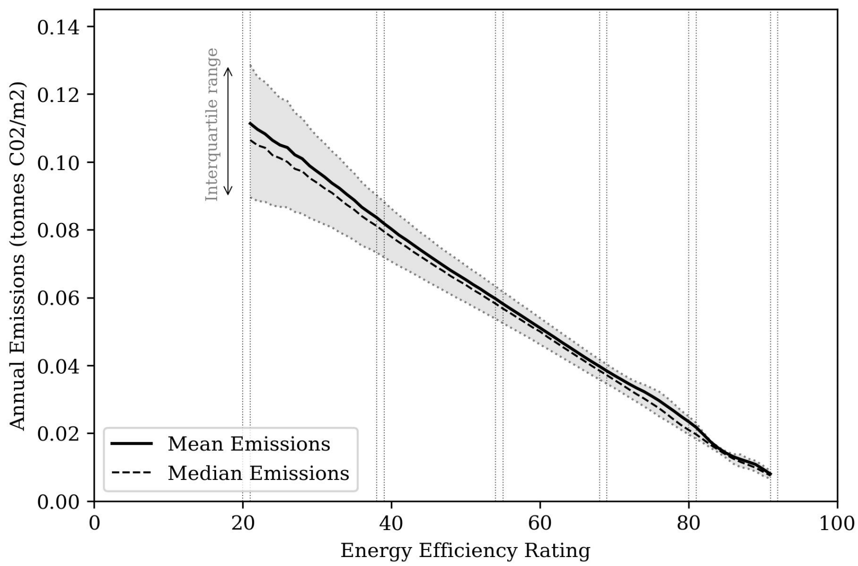
3.3 Environmental impact

EPCs also provide information about the annual carbon emissions of the underlying dwellings. These carbon emissions are transformed into an environmental impact rating from 1 (highest emissions) to 100 (lowest emissions). In practice, homeowners are unlikely to rely on carbon emissions or environmental impact ratings because energy efficiency ratings provide a more holistic view of dwelling sustainability, are easier to interpret, and inform policy decisions.[13] Furthermore, we observe that environmental impact ratings are highly correlated with energy efficiency ratings (95% with a t-statistic of 8.16×10^3), and hence do not contain sufficient incremental information when appraising dwelling sustainability.[14] However, the high correlation between the two measures indicates that insights obtained from examining homeowner valuation of dwelling sustainability can be readily applied to appraise investments in climate change mitigation.

[13] Energy efficiency ratings are the standard metric for communicating dwelling sustainability. For instance, real estate sales and lettings agencies use the infographic corresponding to energy efficiency ratings in Figure 7 to advertise the energy performance of the listings. Similarly, when queried, open-access government lookup tools return the energy efficiency ratings of dwellings. In addition, not all EPCs contain information about carbon emissions or environmental impact ratings on their lead page, which is more heavily scrutinised.

[14] Section IA.2.5 of the Intenet Appendix shows that reestimating hedonic regressions with environmental impact ratings yields approximately identical results as energy efficiency ratings.

Figure 9: Carbon emissions and ratings



This figure shows the annual carbon emissions of dwellings (y-axis), measured in tonnes $C0_2$ per squared meter, corresponding to the energy efficiency of a dwelling (x-axis). The solid (dashed) black line represents the mean (median) annual carbon emissions. The grey shaded area shows the interquartile range.

To this end, it would be instructive to measure how marginal improvements in the energy efficiency rating of a dwelling translate to reductions in annual carbon emissions. Figure 9 shows the annual carbon emissions of dwellings (y-axis), measured in tonnes $C0_2$ per squared meter, corresponding to the energy efficiency of a dwelling (x-axis). The solid (dashed) black line represents the mean (median) annual carbon emissions. The grey shaded area shows the interquartile range. We observe that decreases in annual carbon emissions are approximately linear in increases in energy efficiency ratings. On average, dwellings rated 21 (111 $kgC0_2/m^2$) generate 13.75 times more carbon emissions annually than those rated 91 (8 $kgC0_2/m^2$). We further observe that the interquartile range becomes more concentrated (dispersed) with an increase (decrease) in energy efficiency ratings. This suggests a higher variation in the energy performance of brown dwellings.

Lastly, we regress annual carbon emissions of dwellings on their energy efficiency ratings, and find that a unit improvement in the energy efficiency rating is associated with a reduction of 1.4 $kgC0_2/m^2$ per year, with a t-statisic of -5.17×10^3 and an adjusted R-squared of 79%. As a benchmark, the median dwelling in our sample is rated 65 and generates 43.9 $kgC0_2/m^2$ in emissions per year.

4 Heterogeneity in energy premium

This section examines the spatial, temporal, tenurial, and vintage heterogeneity in the energy premium. The economically meaningful variation in the observed premium supports the use of a valuation model in Section 5 to recover the discount rates that homeowners use to value the energy efficiency of their dwellings.

4.1 Spatial lens

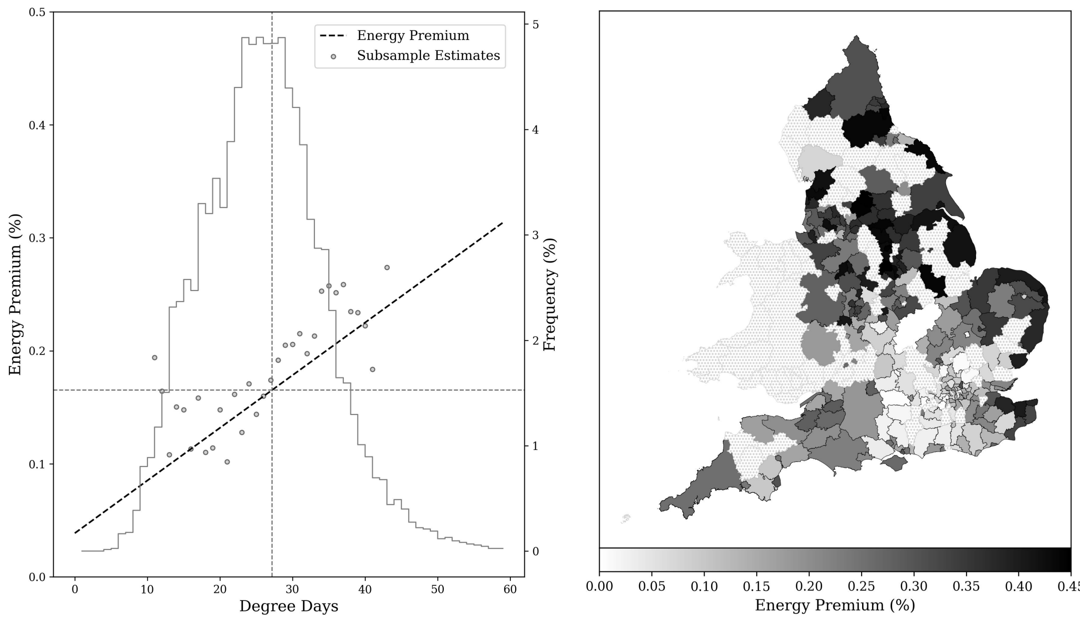
Dwellings with better energy efficiency ratings are expected to consume less energy and thus, incur lower utility expenditures. We posit that homeowners should be willing to pay a higher energy premium in regions where a marginal improvement in the energy performance of the dwelling is expected to yield greater reductions in utility expenditures. We observe from the decomposition of these expenditures that heating (hot water) costs constitute 72.5% (17.3%) of the total utility bill for a typical household in our sample.[15] The heating requirements of a dwelling are directly proportional to the degree days measure corresponding to its location. Hence, we expect properties in regions with higher degree days to benefit from greater energy savings for each unit improvement in energy efficiency rating. This motivates us to examine energy premium conditional on the degree days by augmenting the hedonic regression model in the following manner:

$$\begin{aligned} \log{(P/A)_{ihrt}} = \alpha_r + \delta_t + \xi \mathrm{S}_{ih} + \omega \mathrm{DD}_{rt} + \mu(\mathrm{S}_{ih} \times \mathrm{DD}_{rt}) \\ + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \varepsilon_{ihrt}, \end{aligned} \tag{2}$$

where the unit of observation and the meaning of symbols are same as that in Equation (1). The interaction term between the energy efficiency rating (of property h underlying trans-

[15] We divide the current heating (hot water) expenditures by the total utility expenditures of the dwelling and compute the sample average.

Figure 10: Energy premium conditional on degree days



(a) Conditional estimates **(b) Heatmap**

Panel (a) plots the estimates for energy premium (left y-axis) conditional on degree days (x-axis) obtained from Equation (2), using a dashed black line. The secondary (right) y-axis corresponds to the histogram that shows the distribution of the degree days measure. The cross-hair marked by the intersection of the grey dashed lines represents the unconditional estimate for energy premium (16.54 bps) obtained in Section 3, and corresponds to a region with degree days equal to 27. The circular light-grey markers are obtained by first running separate hedonic regressions (Equation (1), but without the region-specific fixed effect term as r is now fixed) for each borough with at least 10,000 transactions and collecting the region-specific estimates for energy premium. The boroughs are then grouped by their degree days measure rounded to the nearest integer. The markers represent the average value for energy premium in each group. Panel (b) shows the region-specific estimates for energy premium obtained during this procedure through a heatmap. Boroughs marked with a light-grey hatch contain less than 10,000 entries. The values of energy premium correspond to the colour scale provided in the legend at the bottom.

action i) and the degree days measure (for region r in year t) is denoted by $S_{ih} \times \mathrm{DD}_{rt}$, and the corresponding parameter is denoted by μ. The estimate for energy premium for a region with degree days measure d is given by $\hat{\xi} + d\hat{\mu}$.

Panel (a) of Figure 10 plots the estimates for energy premium (left y-axis) conditional on degree days (x-axis) obtained from Equation (2), using a dashed black line. We observe that the premium in regions with degree days equal to 10 is 8.52 bps, and increases 2.6 times to

22.49 bps in regions with degree days equal to 40. The cross-hair marked by the intersection of the dashed grey lines represents the unconditional estimate for energy premium (16.54 bps) obtained in the preceding section, and corresponds to a region with degree days equal to 27. Indeed, the histogram (right y-axis) shows that the density (distribution) of degree days is approximately the highest (centred) around this value.

We corroborate our findings through an alternative methodology. For each borough in our sample with at least 10,000 transactions, we run a separate hedonic regression (Equation (1) without the region-specific fixed effect term as r is now fixed for each borough) and collect the region-specific estimates for energy premium. Then, we round the values for degree days in each borough to the nearest integer, group boroughs by their rounded degree day values, and compute the corresponding energy premium by taking the average of the regional estimates for each group. We refer to these values as subsample estimates, which are plotted using circular light-grey markers in Panel (a) of Figure 10. Notwithstanding minor dispersion, the circular markers are well aligned along the dashed bold line.

Panel (b) of Figure 10 shows the borough-specific estimates for energy premium through a heatmap. We note that the premium is highest in high-altitude and coastal regions, and lowest in inland temperature geographies. Thus, homeowners pay a higher premium in colder regions, where marginal improvements in the energy performance of dwellings are expected to yield greater reductions in utility expenditures. Our findings provide compelling evidence that homeowners value the energy performance of their dwellings in a rational manner.

4.2 Temporal lens

We assume a temporal perspective to examine how energy premium evolves over the duration of our sample using two methodologies. Our first approach involves estimating the following hedonic regression separately for each quarter starting 2010-Q1 until 2020-Q4:

$$\log{(P/A)_{ihrt}} = \alpha_r + \xi_t \mathrm{S}_{ih} + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt} + \varepsilon_{ihrt}, \tag{3}$$

where the unit of observation and the meaning of symbols are same as that in Equation (1), with two differences. First, we drop the time fixed-effects term δ_t as t is now fixed for each of the 44 quarter-specific regressions. Second, we include the subscript t in the parameter associated with the energy efficiency rating, ξ_t, since it is now specific to the period for which the regression is run.

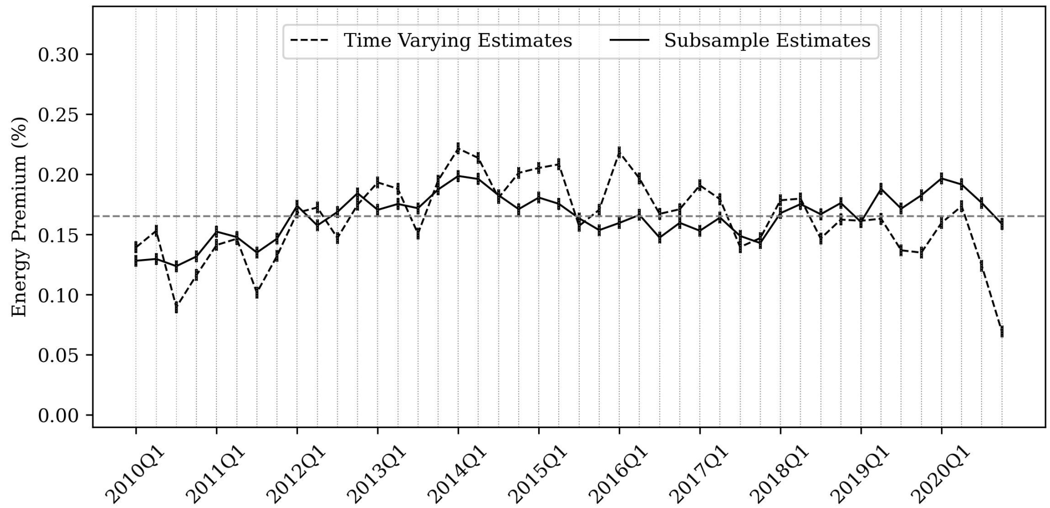
Our second approach is to estimate a single hedonic regression over the full sample, but allow energy premium to vary over time by introducing an interaction term between energy efficiency score and an indicator variable for time, as follows:

$$\begin{aligned}\log{(P/A)_{ihrt}} = \alpha_r + \delta_t + \xi \mathrm{S}_{ih} + \mu_t (\mathbb{1}_t \times \mathrm{S}_{ih}) \\ + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt} + \varepsilon_{ihrt},\end{aligned} \tag{4}$$

where the unit of observation and the meaning of symbols are same as that in Equation (1). The indicator variable for quarter t is denoted by $\mathbb{1}_t$. Hence, the time invariant component of the effect of energy efficiency ratings on property prices is captured by ξ, and μ_t captures the time varying component. For instance, the estimate of energy premium for 2015-Q2 can be computed as $\hat{\xi} + \hat{\mu}_{t=2015\mathrm{Q}2}$. In contrast to the quarter-wise subsample regressions, Equation (4) accounts for the quarter fixed effects δ_t, but forces the estimates for the hedonic covariates to remain constant over the duration of the sample.

Figure 11 shows the quarter-specific estimates for energy premium. The solid black line corresponds to the estimates obtained from the subsample regressions (Equation (3)), while the dashed black line corresponds to the estimates obtained from the interacted-effects model (Equation (4)). The horizontal dashed grey line represents the estimate for energy premium obtained over the full sample (Equation (1) in Section 3). We observe an appreciation in the premium between 2010-Q1 and 2014-Q1 from 12.82 bps to 19.87 bps. This appreciation can be attributed to an increase in the awareness and adoption of energy efficiency ratings after their introduction in 2008-Q4. Thereafter, the values remain fairly close to the unconditional estimate of 16.54 bps. Temporal persistence in the observed premium provides reassurance

Figure 11: Evolution of energy premium



This figure tracks the evolution of energy premium over the duration of our sample. The solid line plots estimates obtained from period-wise subsample regressions in Equation (3). The dashed line plots the estimates obtained from the time-interacted effects model in Equation (4). The horizontal dashed grey line represents the estimate for energy premium obtained over the full sample (Equation (1) in Section 3).

that the energy performance of dwellings is being priced by the market in a consistent manner and that our estimates are not being driven by a specific time period.

4.3 Tenurial lens

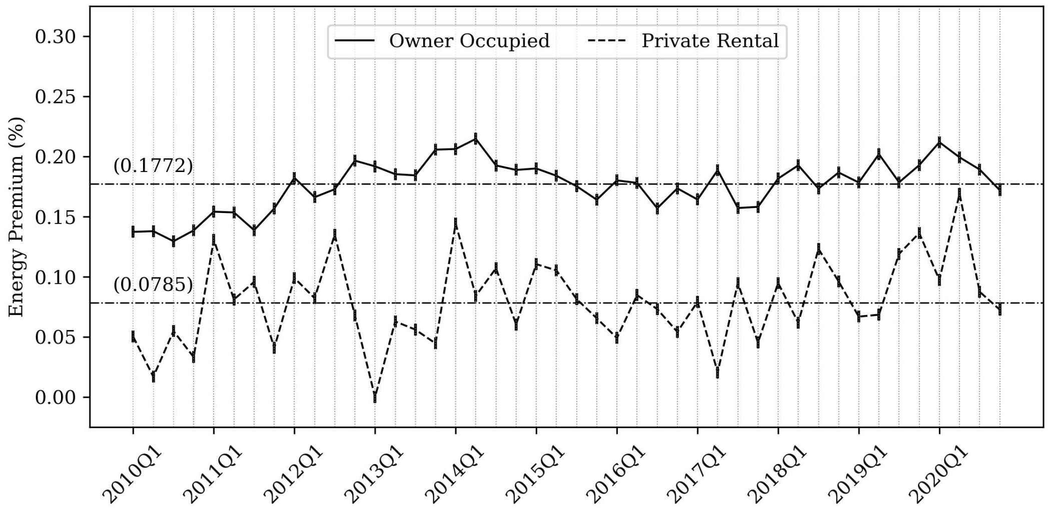
The residential real estate market can be broadly divided into two segments (that is, tenures): owner-occupied (or *buy-to-live*) and private-rental (or *buy-to-let*). Cajias, Fuerst, and Bienert (2019) advocate that these two segments respond heterogenously to energy efficiency ratings. The authors attribute this heterogeneity to the different channels through which buy-to-live homeowners and buy-to-let landlords recoup their investments in energy efficiency. Homeowners who occupy their dwellings can directly recover their investments through reductions in energy expenditures. However, landlords who lease out their properties must recover their investments by transferring these costs to the tenants through higher rents. Thus, the energy premium paid by landlords is contingent on the achievable rental values net of utility costs, which are typically covered by tenants.

Fuerst, Haddad, and Adan (2020) find that improvements in the energy efficiency ratings of dwellings are associated with a higher rental yield in the United Kingdom. Clara, Cocco, Naaraayanan, and Sharma (2024) corroborate this finding, but note that the rental increases are insufficient to offset the capital expenditures required to undertake most improvements. In the context of German rental markets, Cajias, Fuerst, and Bienert (2019) argue that rent caps prevent landlords from sufficiently increasing rental prices. Although the rental market in the United Kingdom has not been subject to similar restrictions over the duration of our sample, several market imperfections prevent landlords from charging higher rents for more energy efficient dwellings.

For instance, information asymmetries can originate from the unwillingness of tenants to incur the attention costs required for acquiring home-specific information due to a shorter residency. The 2020-2021 English Housing Survey reports that the typical length of a dwelling occupancy is 16 years, whereas that for a tenancy is only 4.2 years (UK Government, 2022a). The resultant information asymmetries preclude landlords from credibly communicating the energy efficiency of a property to prospective tenants (Gerarden, Newell, and Stavins, 2017).

The problem is compounded by the provision of fixed price tariffs in the United Kingdom, wherein utility providers charge a fixed tariff each month that does not vary with the monthly energy consumption. These fixed price tariffs depend on the conditions of the energy market and on property sizes, but do not factor in the energy profile of individual dwellings. Utility expenditures are typically covered by the tenants. Therefore, prospective tenants considering fixed-price contracts will be indifferent to dwellings with better energy efficiency ratings since the corresponding reductions in energy consumption will not translate to lower utility costs. Conversely, landlords could continue underinvesting in energy efficiency despite rising utility expenditures (Davis, 2012). Iwata and Yamaga (2008) remark that the heavier utilisation of properties by tenants discourages landlords from undertaking building improvements – such as energy performance – resulting in lower market valuations.

Figure 12: Evolution of energy premium by tenure



This figure tracks the evolution of energy premium – by tenure – over the duration of our sample, obtained from period-wise subsample regressions in Equation (3). The solid line plots estimates obtained for owner-occupied market segment, and the dashed line plots the estimates obtained for the private rental market segment. The two horizontal stippled lines represent the overall segment-specific estimates obtained from Equation (1).

To examine the tenurial heterogeneity in energy premium, we split our dataset by market segment: owner-occupied with 4,792,950 (88.8%) observations and private-rental with 564,939 (10.5%) observations.[16] Then, we estimate period-wise subsample regressions (Equation (3) in Section 4.2) seperately for each segement.[17] The results are shown in Figure 12. Quarterly estimates for energy premium corresponding to the owner-occupied (private-rental) market segments are represented by the solid (dashed) black line. The two horizontal stippled lines represent the overall segment-specific estimates obtained from Equation (1).

[16] We discard the remaining 0.7% observations with tenure as "social rental" because the selling and letting prices for these properties are regulated by the government to provide affordable housing.

[17] Fuerst, McAllister, Nanda, and Wyatt (2015) explain why running regressions separately for the market segments is preferable over estimating a single model with an interaction term between energy ratings and tenure, because there might be systematic differences in the structural characteristics (Iwata and Yamaga, 2008) and energy profile (Rehdanz, 2007) of the housing stock across the two market segments. In addition, the hedonic covariates are expected to be priced differently across the two market segments. For instance, buy-to-let landlords are expected to pay a higher premium for the number of habitable rooms than buy-to-live homeowners, as individual rooms can be rented separately to generate more income.

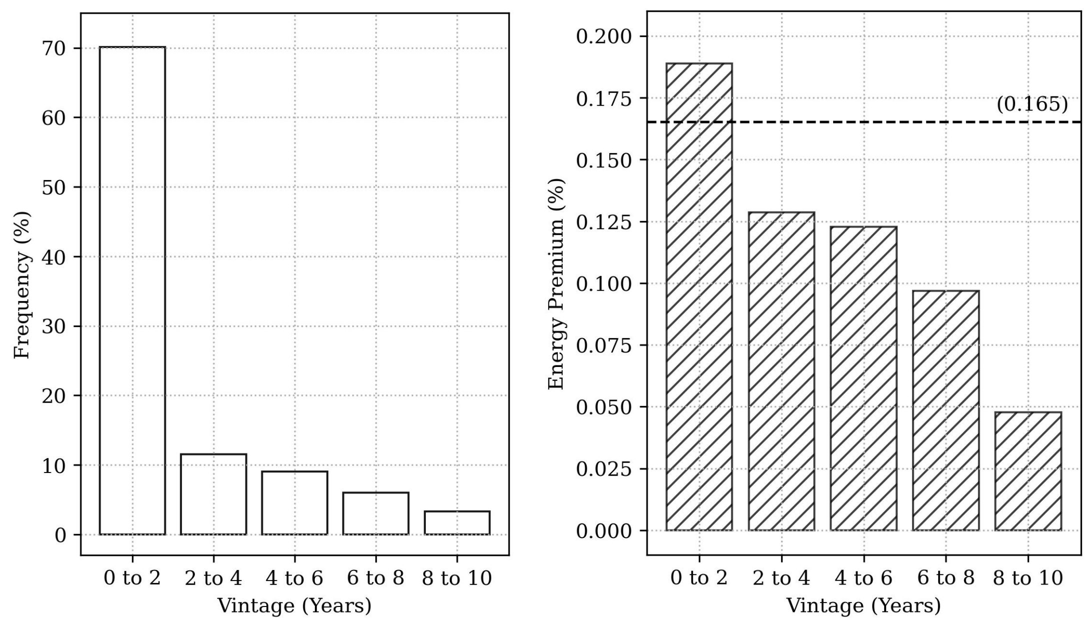
We observe that the energy premium paid by buy-to-let landlords and buy-to-live homeowners is 7.85 bps and 17.72 bps, respectively. Notwithstanding the volatility in the quarterly estimates corresponding to the private-rental market segment – attributable to the smaller period-specific subsamples – the spread in energy premium between the two market segments is temporally persistent. Tables IA.8 and IA.9 in Section IA.3 of the Internet Appendix show that this spread is persistent across regions with different levels of urbanisation and property types, respectively. Finally, we validate that expectations in utility savings from energy efficiency improvements are homogenous across market segments. Thus, differences in these expectations are not driving the spread. Our findings confirm the economic reasoning articulated in extant literature and underscore the meaningful variation in energy premium.

We conclude this section by presenting an alternative vignette to our findings. Bernstein, Gustafson, and Lewis (2019) consider buy-to-let landlords as "sophisticated investors", and argue that landlords purchasing a dwelling for investment (or as a second home) make more informed and rational investment decisions (that is, they exhibit fewer biases in their investment behaviour). This assumption helps them reconcile their findings that when subjected to disaster risk, the discount in property prices observed in the owner-occupied market segment is substantially lower. Therefore, the higher energy premium observed in the owner-occupied market segment could be explained by homeowners overestimating the pecuniary benefits or deriving non-pecuniary benefits from more energy-efficient dwellings.

4.4 Vintage lens

We show that homeowners pay attention to the information contained in Energy Performance Certificates (EPCs) when valuing the energy efficiency of dwellings by exploiting the timing of the certificate issuance. We categorise transactions into five vintages based on the duration between the date of certificate issuance and property sale: 0 to 2 years, 2 to 4 years, 4 to 6 years, 6 to 8 years, and 8 to 10 years. EPCs older than ten years are no longer valid. Panel (a) of Figure 13 shows the frequency of different vintages in our sample. Approximately 70% of EPCs issued are less than two years old at the time of transaction. We observe a stark drop

Figure 13: Energy premium conditional on vintage



(a) Frequency **(b) Conditional premium**

Panel (a) shows the frequency (y-axis) of different vintages (x-axis) in our sample through a bar chart. Transactions are categorised into five vintages based on the duration between the date of certificate issuance and property sale: 0 to 2 years, 2 to 4 years, 4 to 6 years, 6 to 8 years, and 8 to 10 years. Panel (b) reports the results obtained from Equation (5). The bars represent the vintage-specific (x-axis) estimates of energy premium (y-axis). The horizontal dashed line denotes the unconditional estimate obtained from Equation (1) in Section 3.

in the frequency of transactions with older EPCs. Only 3.3% of transactions are associated with EPCs older than eight years. To examine vintage heterogeneity in the energy premium, we estimate the following regression:

$$\begin{aligned}\log{(P/A)_{ihrt}} = \alpha_r + \delta_t + \xi \mathrm{S}_{ih} + \mu_\lambda(\mathbb{1}_\lambda \times \mathrm{S}_{ih}) \\ + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt} + \varepsilon_{ihrt},\end{aligned} \tag{5}$$

where the unit of observation and the meaning of symbols are same as that in Equation (1). The term $\mathbb{1}_\lambda$ denotes the indicator variable for vintage λ, and μ_λ is the parameter associated with the interaction term between $\mathbb{1}_\lambda$ and S_{ih}, the energy efficiency rating. Thus, the energy premium corresponding to a vintage of 2 to 4 years can be obtained as $\hat{\xi} + \hat{\mu}_{\lambda=\text{2-4 years}}$.

Panel (b) of Figure 13 reports the results obtained from estimating Equation (5). The bars represent vintage-specific (x-axis) estimates of energy premium (y-axis). The horizontal dashed line denotes the unconditional estimate obtained from Equation (1) in Section 3. We observe that the energy premium corresponding to older (newer) vintages is lower (higher). The premium is 18.89 bps when the vintage is 0 to 2 years, which is close to the unconditional estimate of 16.54 bps. It attenuates to a range from 10 to 13 bps for vintages between 2 and 8 years, and reduces to only 4.78 bps when the vintage is 8 to 10 years. These observations suggest that homeowners perceive EPCs with newer vintages to contain more accurate and reliable information about the energy performance of the underlying dwelling. More broadly, the observations indicate that homeowners use EPCs to appraise dwelling sustainability.

5 Discount rates and green premium

Motivated by the economically meaningful variation in the energy premium observed in the preceding sections, this section presents a simple valuation framework to recover the discount rates that homeowners use to value the energy efficiency of their dwellings. The approach is adopted from Giglio, Maggiori, and Stroebel (2015). Our main objective is not to develop a new economic or asset pricing model but to examine what a simple valuation approach can tell us about societal preferences from private decisions.

5.1 Valuation framework

Consider two otherwise identical dwellings with energy efficiency ratings s and $s+1$, respectively. The difference in these ratings indicates a marginal improvement in energy efficiency, which translates into lower utility expenditures. We denote the expected utility savings as:

$$\mathbb{E}[\Delta U(s, s+1)] = \mathbb{E}[U(s) - U(s+1)], \tag{6}$$

where $U(s)$ represents total annual utility expenditure of the dwelling with energy efficiency rating s. Section 4.1 provides evidence that homeowners price marginal improvements in the energy performance of dwellings based on expected utility savings. Therefore, if we interpret these annual utility savings as dividends paid in perpetuity and discount them at a constant *marginal* rate $r(s, s+1)$, the present value of these savings can be equated to the difference in prices between the two dwellings, $\Delta P(s, s+1) := P(s+1) - P(s)$, as follows:

$$\Delta P(s, s+1) = \frac{\mathbb{E}[\Delta U(s, s+1)]}{r(s, s+1) - g}, \tag{7}$$

where g is the growth rate of utility savings. Equation (7) is the Gordon (1982) growth model for infinitely lived assets. The discount rate $r(s, s+1)$ is conditioned on s, and thus captures the *marginal preference* corresponding to a unit improvement in the energy efficiency rating of a dwelling from s to $s+1$. This enables us to capture the cross-sectional heterogeneity in preferences between homeowners who purchase green versus brown dwellings. For exposition, we rearrange the equation and divide the numerator and the denominator by dwelling price with energy efficiency rating s as follows:

$$r(s, s+1) - g = \frac{\mathbb{E}[\Delta U(s, s+1)] \,/P(s)}{\Delta P(s, s+1) \;\;/P(s)} = \frac{\Delta u(s, s+1)}{\Delta p(s, s+1)}, \tag{8}$$

such that the relationship between the term in the denominator and energy premium becomes more transparent. We calibrate $\Delta p(s, s+1)$ using $\hat{\xi}$ obtained from estimating Equation (1) on transactions with a freehold covenant. Freeholds are perpetual ownership contracts and constitute approximately 80% of our baseline regression sample. We recover the net discount rates using expectations of marginal utility savings computed in Section 5.2 and report the results in Sections 5.3.

5.2 Computing expected marginal savings and premia

We now describe the methodology to obtain expected marginal savings. Let us denote each transaction in our sample with $i \in I$, such that $|I|$ is the number of entries in the sample. For transaction i, we denote the current and potential energy efficiency ratings of the underlying dwelling as S_i^{current} and $S_i^{\text{potential}}$, respectively. Similarly, we denote the current and potential annual utility expenditures associated with the underlying dwelling as U_i^{current} and $U_i^{\text{potential}}$, respectively. It follows that $S_i^{\text{current}} \leq S_i^{\text{potential}}$ and $U_i^{\text{current}} \geq U_i^{\text{potential}}$.

Lastly, $\Delta U_i(s, s+1)$ denotes the incremental utility savings from a marginal improvement in the energy efficiency rating of dwelling i from s to $s+1$. We assume that $\Delta U_i(s, s+1)$ is uniform between S_i^{current} and $S_i^{\text{potential}}$, and compute it as follows:

$$\Delta U_i(s, s+1) = \frac{U_i^{\text{current}} - U_i^{\text{potential}}}{S_i^{\text{potential}} - S_i^{\text{current}}}, \quad S_i^{\text{current}} \leq s < S_i^{\text{potential}}. \tag{9}$$

We note that for a given observation i, $\Delta U_i(s, s+1)$ only exists for values of s between the current and potential energy efficiency ratings of the underlying dwelling and is not defined when $S_i^{\text{current}} = S_i^{\text{potential}}$. For each s, we represent the set of observations for which $U_i(s, s+1)$ exists as $I(s)$. To obtain the expected utility savings from a marginal improvement in energy efficiency rating from s to $s+1$, we average over $I(s)$ as follows:

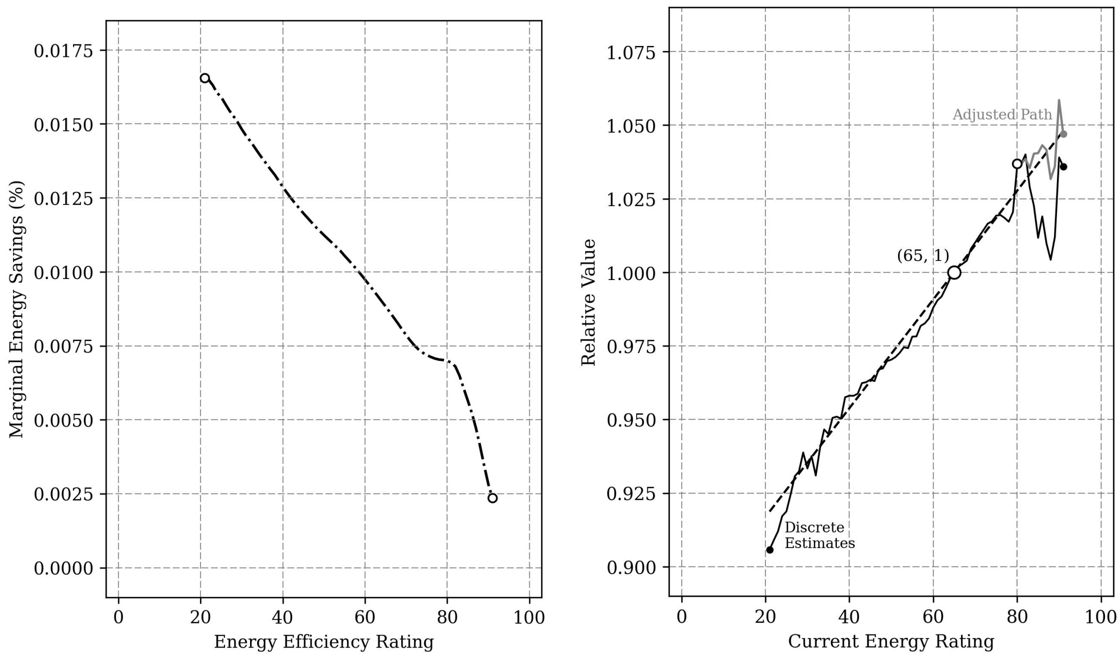
$$\Delta u(s, s+1) = \frac{1}{|I(s)|} \sum_{s \in I(s)} \Delta u_i(s, s+1), \tag{10}$$

where $\Delta u_i(s, s+1) := \Delta U_i(s, s+1)/P_i$.[18] Panel (a) of Figure 14 reports the marginal utility savings obtained from Equation (10). The y-axis represents the marginal savings, expressed as a proportion of property price, obtained from improving the energy efficiency rating from the value shown in the x-axis by one unit. The graph shows declining returns with subsequent increases in energy performance. The expected savings obtained from a marginal increase in the energy efficiency of a dwelling rated 91 (0.24 bps) are 7.3 times lower than those obtained from a dwelling rated 21 (1.75 bps).

We calibrate $\Delta p(s, s+1)$ in Equation (8) to 18.47 bps, which is the estimate of ξ obtained from Equation (1) using 80% of the transactions in our data with a freehold covenant. The main concern with our choice of calibration is that it implicitly assumes that $\Delta p(s, s+1)$ is invariant with s. Given the declining structure of the graph for marginal utility savings, we might expect a declining marginal premia from subsequent improvements in energy efficiency. However, Figure IA.8 in Section IA.2.2 of the Internet Appendix shows that the expectation

[18] Overall, our approach yields two advantages. First, it enables us to compute marginal savings (expressed as a percentage of dwelling price) from a unit improvement in energy efficiency while keeping the underlying dwelling *fixed* before the aggregation step. This is useful because prices are also simultaneously determined by other hedonic covariates. Second, for each dwelling, this approach also extracts marginal savings figures for a range of energy efficiency ratings and not only the current rating assigned to the dwelling. This increases the number of observations corresponding to each rating conditional on which the expectation is computed.

Figure 14: Marginal savings and premia



(a) Marginal savings **(b) Marginal premia**

Panel (a) shows the marginal utility savings obtained from Equation (10) using a stipped black line. The y-axis represents the marginal savings, expressed as a proportion of property price, obtained from improving the energy efficiency rating from the value shown in the x-axis by one unit. Panel (b) shows the implied value (y-axis) of a dwelling with a given rating (x-axis) *relative* to a dwelling rated 65 (the median rating in the sample). The diagonal dashed black line represents the relative valuation of dwellings obtained from Equation (1) estimated on a sample of transactions with a freehold covenant. The solid black line represents the relative valuation obtained from a modified version of Equation (1) with each energy efficiency rating treated as a distinct categorical variable. The solid grey line represents relative valuations obtained from the modified model on a sample of dwellings with ratings between 81 and 91.

of the residuals obtained from Equation (1), conditioned on energy efficiency ratings, remains close to zero. This indicates that dwelling prices have a linear relationship with the ratings.

Notwithstanding, we further validate that $\Delta p(s, s+1)$ is invariant with s by estimating Equation (1) with energy efficiency ratings treated as a distinct categorical variable. Hence, the coefficient associated with each numerical rating is estimated separately. The differences in estimates corresponding to subsequent energy efficiency ratings provide the most granular and parametrically unconstrained measure for marginal energy premia. The solid black line in Panel (b) of Figure 14 represents the predictions obtained from the modified specification. The y-axis corresponds to the value of a dwelling rated on the x-axis relative to a dwelling rated 65 (the median rating in our sample). Hence, the relative value of a dwelling rated 65 is one. The diagonal dashed black line represents the relative valuation of dwellings obtained from our original specification.

We observe that the solid black line is well aligned with the dashed black line, supporting our choice of calibration. In addition, we also note a drop in the solid black line corresponding to dwellings rated between 83 and 89, followed by a sharp reversion to the dashed black line. This highlights the limitations of the parametrically flexible approach. Heterogeneity in the composition of dwellings across different ratings can coerce rating-specific fixed effects (that is, individual coefficients of numerical ratings) to absorb the effect of other covariates which are negatively correlated with dwelling prices. For example, the built form of the properties rated between 83 and 89 could belong to a less desirable category. To examine whether this rationale is behind the trough in the graph, we run the modified specification on a sample of dwellings rated between 81 and 91 and plot the predictions obtained from the homogenised sample with a solid grey line in the figure.[19] The trough attenuates, and the graph realigns with the predictions obtained from the original specification.

5.3 Implied net discount rates

This section discusses the conditional and unconditional net discount rates implied by our valuation framework.

5.3.1 Marginal rates and "green premium"

Figure 1 reports the marginal net discount rates obtained from Equation (8) using a stippled black line. The y-axis corresponds to the rate $r(s, s+1)-g$ that homeowners use to discount marginal savings from a unit improvement in the energy efficiency rating of dwellings rated s

[19] We chose a range between 81 and 91 because it cleanly corresponds to the range of dwellings sorted into the alphabetical label B (see Figure 7 in Section 3).

on the x-axis. On average, homeowners discount utility savings from a marginal improvement in the energy efficiency of a dwelling rated 80 (40) at 3.79% (6.97%). The downward-sloping graph implies that homeowners are willing to accept lower returns for greener dwellings. We term this difference as the *green premium*, which can be interpreted as non-pecuniary benefits derived by homeowners from dwelling sustainability.

5.3.2 Aggregate rates, climate change, and policy implications

Homeowners use an aggregate net discount rate of 4.43% to value dwelling energy efficiency. We obtain the aggregate value by computing the unconditional expectation of the measures for marginal utility savings computed in Section 5.2 and dividing it by the energy premium. Dwellings are specifically exposed to climate-related risks which are reflected in their prices (Baldauf, Garlappi, and Yannelis, 2020; Giglio, Maggiori, Rao, Stroebel, and Weber, 2021). Therefore, discount rates recovered from homeowner valuation of dwelling energy efficiency can provide direct measures for the rates used to appraise investments in sustainable development and, more broadly, climate change mitigation.

There is a widespread disagreement in the literature on the appropriate rate that should be used to discount public investments in climate change abatement. Stern (2007) advocates a rate of 1.4%, with a view of intergenerational equity. Lower rates assign greater value to the welfare of future generations. In contrast, Nordhaus (2007) argues that a rate of 5.5% is more appropriate from an empirical standpoint. Higher rates reflect the view that capital is scarce, and climate investments compete with alternative valuable investments in societies (Nordhaus, 2013). Groom and Maddison (2019) remark that the divergence in discount rates can be attributed to differences in the interpretation and the measurement of the parameters used in the underlying economic models.[20] They propose a short (long) rate of 4.5% (4.2%). The aggregate rate that we recover is consistent with Groom and Maddison (2019).[21]

[20]Economists typically use the Ramsey (1928) rule to compute discount rates used for public interventions, which is driven by three parameters: (i) pure rate of time preference, (ii) consumption growth, and (iii) the elasticity of marginal utility. Stern (2007) and Nordhaus (2007) calibrate the pure rate of time preference to 0.1% and 1.5%, respectively.

[21]The manner in which the unconditional expectation of utility savings is computed has an impact on the implied aggregate net discount rate. In our calculation, we simply average over all ratings and all dwellings.

In comparison, the value adopted in official guidance by the UK Government (2022b) is 3.5%. Setting the discount rate too high could prevent socially desirable projects from being undertaken (Zhuang, Liang, Lin, and De Guzman, 2007). Hence, regulators may strategically but understandibly select lower values to make public undertakings more attractive. However, setting the value too low could result in a suboptimal policy design. For instance, consider the 'Green Deal' introduced by the UK Government in 2013, which offered loans to homeowners to improve the energy efficiency of their dwellings. The rationale behind the loans was that the resultant expected utility savings would offset the cost of the repayments. The National Audit Office (2016) reports that the annual utility savings from improving loft insulation were estimated to be £15. Our valuation framework implies a present value equal to £338 (£428) when these savings are discounted at 4.43% (3.5%). Therefore, the regulator would overestimate the benefits of the scheme by 25%, relative to homeowners. The scheme was discontinued in 2015 following a low uptake.

Unlike the regulator who wishes to optimise social welfare, homeowners could be expected to assume a myopic view and perceive improvements in dwelling energy efficiency as private investments. They may also be exposed to project- or property-specific risks that cannot be diversified away. As a result, the higher discount rate observed in the residential real market could be attributed to a higher marginal rate of return on investment in the private sector. Therefore, while it may be appropriate for regulators to continue using lower discount rates to support socially desirable projects, the rates applied for projects where public and private sectors compete for the same pool of funds should reflect the opportunity cost of capital in the private sector.

This approach is straightforward. However, because we assume that marginal savings are uniform between current and potential energy efficiency ratings of dwellings, we implicitly double-count them or put differently, overweight estimates obtained from dwellings with higher upgradeability. To address this, we can first average marginal savings over each dwelling and then take the mean of dwelling-specific measures. This results in an implied net discount rate of 4%, which equals the value that Nordhaus (2013) uses to calibrate his dynamic integrated climate-economy (DICE) model. However, this method does not equally weight homeowners with heterogenous preferences. To address this, we must reverse the procedure—that is, take the mean of rating-specific conditional averages reported in the preceding section. This yields a net discount rate of 5.6%, which is very close to what Nordhaus (2007) proposes.

6 Demand for energy efficiency and regulatory impact

In this section, we examine homeowner decisions to improve the energy performance of their dwellings, and how these decisions are influenced by a regulation passed by the government to improve the energy profile of the housing stock in the United Kingdom. Section 6.1 looks at the cost, the likelihood, and the magnitude of energy efficiency improvements. Section 6.2 describes the regulation and documents its impact on the likelihood of upgrades, the energy premium, and dwelling prices.

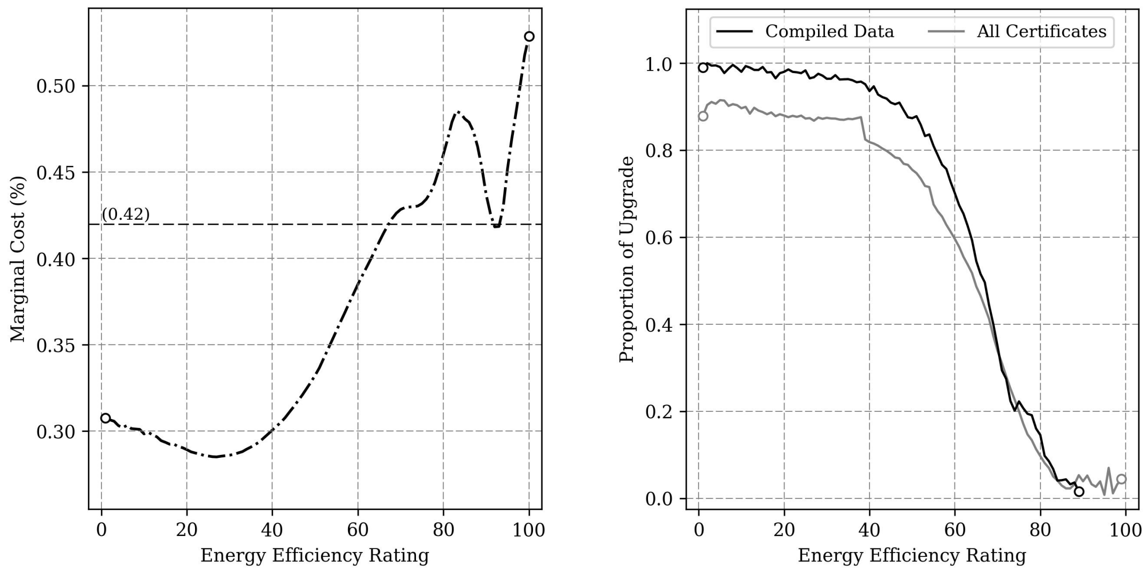
6.1 Marginal costs and the energy performance upgrades

Panel (a) of Figure 15 shows the marginal costs (y-axis) associated with improving the energy performance of the dwelling (x-axis) by one unit, expressed as a proportion of property price. We obtain marginal costs analogously to how marginal savings were obtained in Section 5.2.[22] The graph shows that subsequent improvements in energy performance become progressively more expensive. The cost associated with a unit improvement in the energy performance of a dwelling rated 80 (46 bps) is 1.5 times more than that of a dwelling rated 40 (30 bps). The horizontal line represents the unconditional value (42 bps) taken over the complete sample. We observe that marginal costs are substantially higher than the estimated energy premium (16.54 bps). Hence, the market does not compensate homeowners sufficiently for improving the energy performance of their dwellings.

Increasing marginal costs and decreasing marginal savings suggest that greener dwellings are less likely to have their energy efficiency ratings upgraded. This reasoning is corroborated in Panel (b) of Figure 15. For the 226,829 dwellings that were transacted twice in our sample, and had a certificate issued between the first and the second transaction, the solid black plots the proportion of properties (y-axis) that had their energy efficiency ratings upgraded against their initial rating (x-axis). Approximately 98% (14%) of dwellings rated 20 (80) had their

[22] When computing marginal costs, we obtain the *median* in the aggregation step because dwellings with low upgradeability inflate the mean; computing the mean instead further strengthens our results.

Figure 15: Marginal costs and likelihood of upgrade



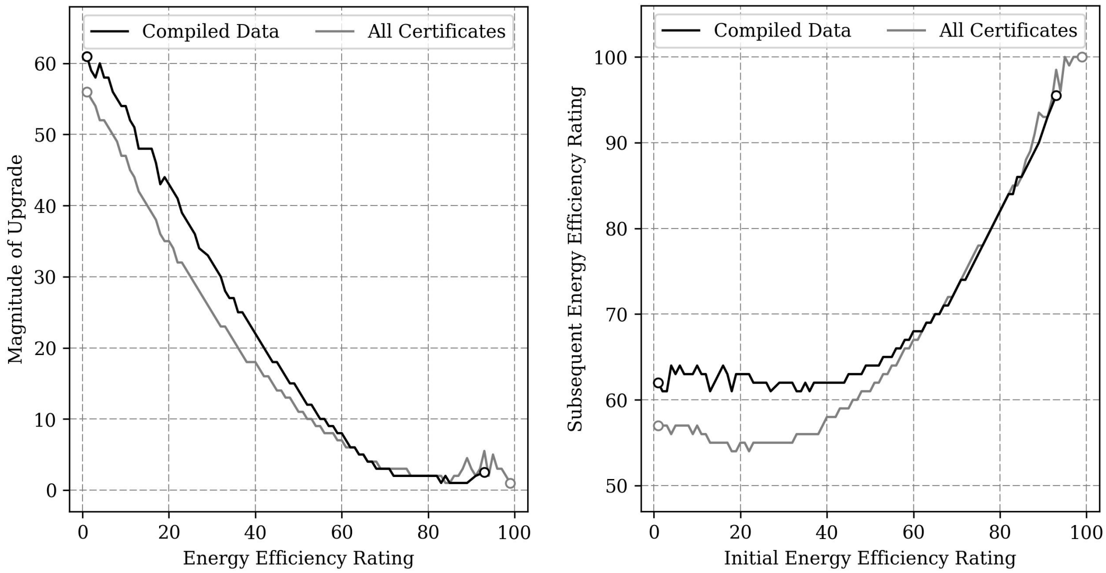
(a) Marginal cost of anupgrade **(b) Proportion of upgrades**

Panel (a) shows the marginal costs (y-axis) associated with improving the energy efficiency of a dwelling (x-axis) by one unit, expressed as a proportion of property price. The marginal costs are obtained analogously to how the marginal savings were computed in Section 5.2. Panel (b) shows the proportion of properties (y-axis) that had their ratings improved against their initial rating (x-axis) using a solid black line. The analysis is performed for 226,829 dwellings that were transacted twice in the compiled sample, and had a certificate issued between the first and the second transaction. The solid grey line reproduces the analysis for 2,871,736 dwellings that had exactly two EPCs recorded in the Energy Performance of Buildings Register.

ratings upgraded prior to the second transaction. Our sample only contains the most recent certificate corresponding to a sale recorded in the HM Land Registry. However, a subsequent certificate issuance may not be followed by a transaction. Therefore, we replicate our analysis for the 2,871,736 dwellings that had exactly two EPCs recorded in the Energy Performance of Buildings Register. The solid grey line plots the results. The initial divergence between the two graphs signals that lower-rated dwellings are more likely to have their ratings upgraded when the subsequent issuance is followed by a transaction.

Next, we examine the magnitude of energy efficiency improvements between subsequent certificate issuances. The solid black line in Panel (a) of Figure 16 plots the median difference (y-axis) in the energy efficiency rating of dwellings between subsequent issuances against their

Figure 16: Magnitude of energy performance upgrades



(a) Magnitude of upgrade **(b) Initial and subsequent ratings**

Panel (a) shows the median difference (y-axis) in the energy efficiency rating of dwellings between subsequent EPC issuances against their initial rating (x-axis). Panel (b) shows the median rating corresponding to the second certificate (y-axis) against that of the first certificate (x-axis). The solid black lines in the panels correspond to the analysis performed for 226,829 dwellings that were transacted twice in the compiled sample, and had a certificate issued between the first and the second transaction. The solid grey lines reproduce the analysis for 2,871,736 dwellings that had exactly two EPCs recorded in the Energy Performance of Buildings Register.

initial rating (x-axis). Dwellings initially rated 20 (80) had their ratings improved by 43 (2) points. The solid black line in Panel (b) of Figure 16 plots the median rating corresponding to the second certificate (y-axis) against that of the first certificate (x-axis). Dwellings initially rated 20 (80) were subsequently rated 63 (82), consistent with Panel (a). Our findings show that lower rated dwellings undergo larger energy performance improvements. We reproduce the analysis for the universe of certificates in the Energy Performance of Buildings Register, and report the results using solid grey lines in Panels (a) and (b) of Figure 16, respectively. Our conclusions remain the same. As before, the initial divergence between the black and the grey graphs indicates that lower-rated dwellings undergo larger rating improvements when the subsequent issuance is followed by a transaction.

6.2 Regulatory impact

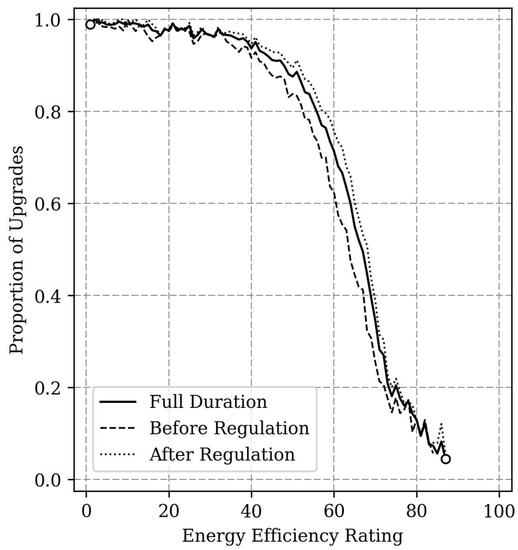
An examination of tenurial heterogeneity in Section 4.3 shows that buy-to-let landlords and buy-to-live homeowners respond heterogeneously to dwelling energy efficiency. Reproducing the analysis in Section 5.3.2 by tenure shows that the aggregate rate used to discount expected utility savings used in the owner-occupied (private-rental) market segment is 4.21% (11.03%). This spread in preferences is consistent with extant literature that notes an underinvestment in energy performance in the private-rental market segment (Iwata and Yamaga, 2008; Davis, 2012; Gerarden, Newell, and Stavins, 2017). On March 26, 2015, the UK Government (2017) introduced a Minimum Energy Efficiency Standard (MEES) to address this underinvestment. The policy stated that new (existing) tenancies cannot be granted (extended) after April 1, 2018 for properties rated below 39. The policy further stated that properties rated below 39 cannot continue being leased out starting April 1, 2020.

6.2.1 Impact on energy performance improvements

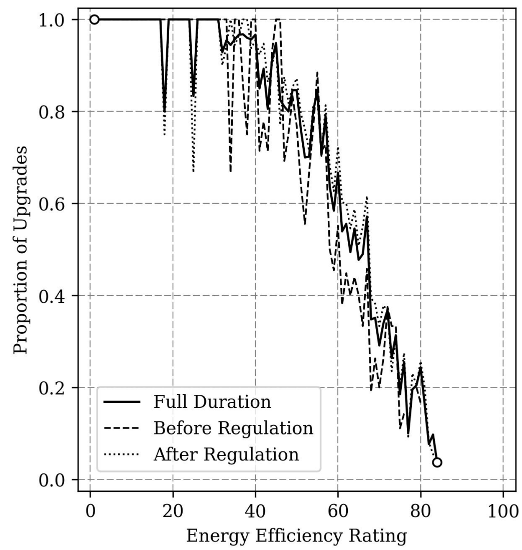
This section examines regulatory impact on homeowner decisions to improve dwelling energy efficiency. Figure 17 replicates the analysis in Panel (b) of Figure 15 for owner-occupied and private-rental market segments before and after the regulation. For owner-occupied dwellings that were transacted twice in our sample, and had a certificate issued between the first and the second transaction, the solid black line in Panel (a) of Figure 17 represents the proportion of dwellings that had their ratings improved (y-axis) against their initial rating (x-axis). The dashed (dotted) line plots the proportion of upgrades for dwellings that had their certificate issued before (after) the regulation was introduced. Panel (b) replicates Panel (a) for private-rental properties. Panels (c) and (d) reproduce the analysis in Panel (a) and (b), respectively, for the universe of dwellings in the Energy Performance of Buildings Register for which two certificates were issued but not necessarily followed by a transaction.

We observe across all four panels that higher-rated dwellings are less likely to have their ratings improved. The level differences between the graphs in the top and the bottom panels

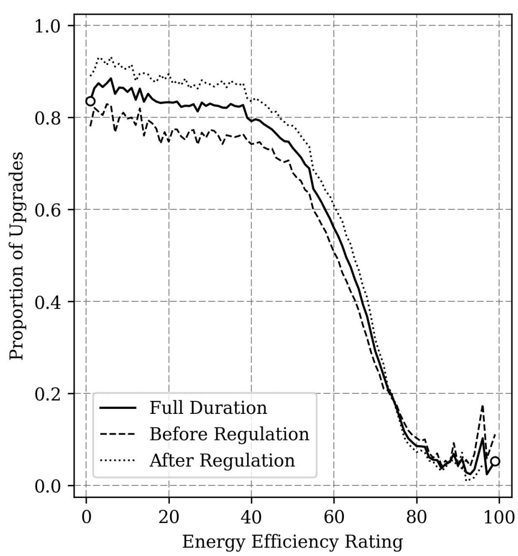
Figure 17: Cross-sectional likelihood of an improvement



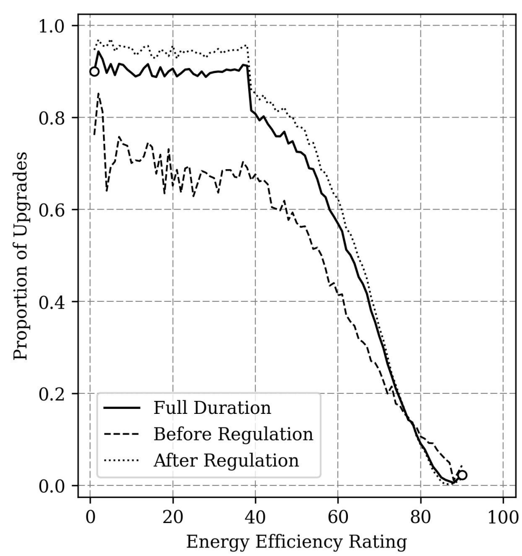
(a) Owner-occupied (compiled data)



(b) Private-rental (compiled data)



(c) Owner-occupied (all certificates)



(d) Private-rental (all certificates)

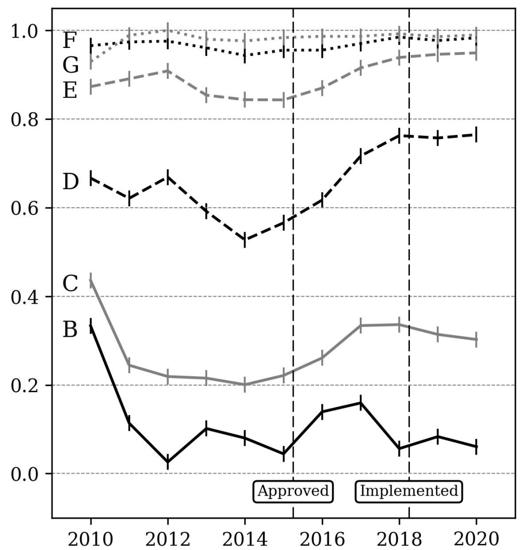
For the owner-occupied dwellings that were transacted twice in the compiled sample, and had a certificate issued between the first and the second transaction, the solid black line in Panel (a) represents the proportion of dwellings that had their ratings improved (y-axis) against their initial rating (x-axis). The dashed (dotted) line plots the proportion of upgrades for dwellings that had their certificate issued before (after) the regulation was introduced. Panel (b) replicates Panel (a) for private-rental properties. Panels (c) and (d) reproduce the analysis in Panel (a) and (b), respectively, for the universe of dwellings in the Energy Performance of Buildings Register for which two certificates were issued.

indicate that lower-rated dwellings are more likely to have their ratings improved when the subsequent issuance is followed by a transaction. These observations are aligned with those in the preceding section. Consistent with Clara, Cocco, Naaraayanan, and Sharma (2024), the initial divergence between the dashed and the dotted lines in Panel (d) shows that lower-rated private-rental properties were more likely to have their ratings improved post-regulation. The discontinuity in the dotted line between properties initially rated 38 and 39 emphasises the regulatory threshold. However, we observe that private-rental properties rated 39 or above were also more likely to have their ratings improved post-regulation. Furthermore, Panel (c) shows that lower-rated owner-occupied dwellings were also more likely to have their ratings improved post-regulation. An increase in the likelihood of energy efficiency improvements for dwellings not targeted by the regulation suggests that government intervention indirectly led to an increase in the demand for greener dwellings. Lastly, a modest divergence between the dashed and the dotted lines in the top two panels reveals that, although the likelihood of a rating improvement is higher when certificate issuances are followed by a sale, this likelihood does not increase substantially post-regulation.

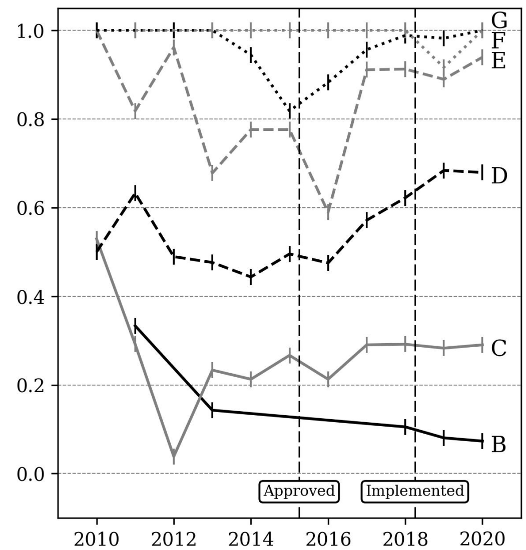
We further scrutinise the regulatory impact by assuming a temporal vignette. To examine how the likelihood of energy performance improvements evolves, we cluster energy efficiency ratings into their corresponding alphabetical labels (see Figure 7 in Section 3) from G (least sustainable) to B (most sustainable).[23] For each cluster, we then compute the proportion of dwellings that had their ratings improved in each calendar year. The results are reported in Figure 18. Panels (a) and (b) trace the likelihood of an improvement for the owner-occupied and private-rental market segments, respectively, over the duration of our sample. As before, Panels (c) and (d) reproduce the analysis for the Energy Performance of Buildings Register. From left to right, the vertical dashed lines demarcate policy approval (March 16, 2015) and enforcement (April 1, 2018), respectively. Consistent with the cross-sectional vignette, Panel (d) shows that private-rental properties labelled F and G (labels that correspond to a rating below 39) were more likely to have their ratings improved post-regulation. However, we

[23] We exclude label A due to the insufficient number of dwellings required to perform a temporal analysis.

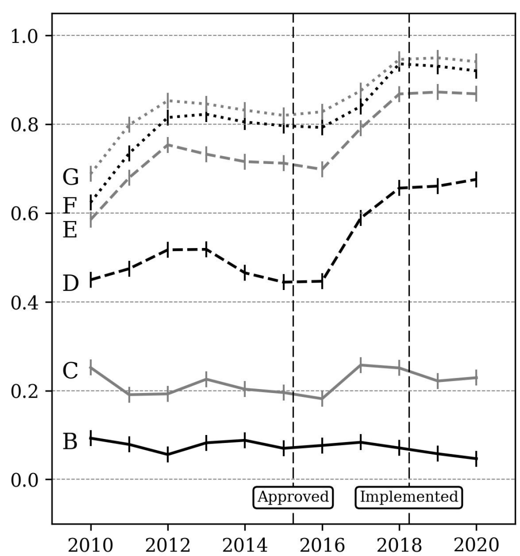
Figure 18: Likelihood of improvements over time



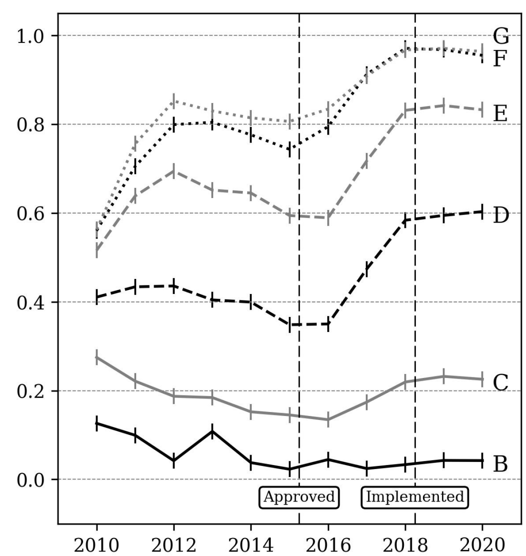
(a) Owner-occupied (compiled data)



(b) Private-rental (compiled data)



(c) Owner-occupied (all certificates)



(d) Private-rental (all certificates)

This figure shows the proportion of properties that had their energy ratings upgraded in each year for each initial energy efficiency label. Panel (a) and (b) show results for owner-occupied and private-rental properties that were transacted exactly twice in our compiled sample and had a new energy certificate issued prior to the second transaction. Panels (c) and (d) replicate the results for the universe of dwellings in the Energy Performance of Buildings Register for which two certificates were issued. The vertical dashed black lines denote policy approval (March 26, 2015) and enforcement (April 1, 2018), respectively.

Table 3: Changes in the likelihood of an improvement after regulation

		All	B	C	D	E	F	G
Compiled data	Both segments	0.00	-0.01	-0.00	0.00	-0.00	0.00	0.00
	Owner occupied	0.00	-0.01	-0.00	0.00	-0.00	0.00	-0.00
	Private rental	-0.01	-0.01	0.01	-0.01	-0.01	0.01	0.01
All certificates	Both segments	0.07***	-0.04***	0.02***	0.11***	0.11***	0.14***	0.12***
	Owner occupied	0.08***	-0.03***	0.02***	0.10***	0.10***	0.12***	0.11***
	Private rental	0.09***	-0.05***	0.02***	0.15***	0.16***	0.20***	0.16***

This table reports the change in the probability of a rating improvement for a dwelling belonging to a given market segment and label after the regulation was introduced. The values are based on the predictions from Equation (IA4) described in Section IA.4.1 of the Internet Appendix. The top panel corresponds to the results obtained for dwellings that were transacted twice in our compiled data and had a new certificate issued prior to the second transaction. The bottom panel replicates the results for the universe of dwellings in the Energy Performance of Buildings Register for which two certificates were issued but were not necessarily followed by a transaction. Lastly, p-values less than 0.10, 0.05, and 0.01 are demarcated by one (*), two (**), and three (***) stars, respectively.

also note a similar trend for properties labelled E, D, and C (labels corresponding to ratings 39 and above). Panel (c) further shows an increase in energy performance improvements for owner-occupied dwellings labelled G through C. Overall, we observe a steady appreciation in graphs between the regulatory approval and implementation, followed by a plateau. Finally, Panels (a) and (b) corroborate that the likelihood of a rating improvement is higher (nearly 100% for dwellings labelled G) when certificate issuances are followed by a transaction, but this likelihood does not increase post-regulation.

To formalise our findings, we estimate a logistic regression to measure the change in the probability of an improvement for a dwelling, belonging to a given market segment and label, after the regulation was introduced. The details are deferred to Section IA.4.1 of the Internet Appendix. For each market segment and label, Table 3 reports the changes in the probability of an improvement after the regulation was approved, relative to the period before. Overall, we note (i) a statistically significant increase in the likelihood of an improvement across both owner-occupied (8%) and private-rental (9%) markets and (ii) an insignificant impact on the likelihood of improvement corresponding to issuances followed by a transaction. In addition, we observe that dwellings labelled B were less likely to have their ratings improved after the regulation was introduced.

6.2.2 Impact on energy premium

The quarter-specific estimates shown in Figure 11 in Section 4.2 suggest that the regulation did not impact the energy premium. The spatial analysis performed in Section 4.1 indicates that homeowners price dwelling energy efficiency based on expected utility savings. Because the regulation does not have an impact on these savings, it follows that it should not have an impact on the price of dwelling energy efficiency. In this section, we formalise this intuition to underscore the economically meaningful variation in energy premium and further rationalise the use of our valuation model.

To measure the impact of the regulation on energy premium, we augment Equations (4) in Section 4.2 to include a regulation-specific fixed effect for the period following its introduction on March 26, 2015. We obtain an estimate of 0.45 bps with a p-value equal to 0.88. Hence, the impact of regulation on energy premium is both economically and statistically insignificant. One concern with our analysis is that the time-specific fixed effects in Equations (4) absorb the effect of the regulation. To address this concern, we estimate Equations (1) in Section 3.1 in a similar manner, and obtain a regulation-specific fixed effect of -0.17 bps with a p-value equal to 0.85. This verifies that the regulation did not impact the energy premium.

6.2.3 Impact on prices of targeted dwellings that did not upgrade

Of the 411,869 (184,054) private-rental properties in our compiled data that transacted after the regulation was approved (implemented), 3.85% (2.99%) properties were rated below 39. To continue being leased out, these properties must have their ratings improved, which incurs capital expenditure. In this section, we investigate whether these properties were transacted at (an additional) discount post-regulation using two methodologies.

Our first methodology is *difference in differences*, which is a quasi-experimental technique that mimics an experimental research design using observational study data (see Angrist and Pischke (2008, Chapter 5.2). It assumes that, in the absence of treatment, the differences in potential outcomes between the treatment and control groups are the same before and after the implementation of the regulation.[24] Hence, the methodology is applicable in our context if we assume that, in the absence of regulation, the price evolution of properties rated 39 or higher (the control group) is parallel to those rated below 39 (the treatment group), holding all else equal. If we further assume that the regulation and treatment effects are linear and additive, we can extend Equation (4) in Section 4.2 into a difference in differences setup and estimate the following model:

$$\begin{aligned}\log{(P/A)_{ihrt}} = \alpha_r + \delta_t + \xi \mathrm{S}_{ih} + \mu_t(\mathbb{1}_t \times \mathrm{S}_{ih}) \\ + \lambda_{\text{Regulation}} + \rho_{\text{Regulation}} X_i \\ + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt} + \varepsilon_{ihrt},\end{aligned} \tag{11}$$

where $\lambda_{\text{Regulation}}$ denotes the regulation fixed effect on the target variable (for both treatment and control groups) and X_i is an indicator variable for treatment; $X_i = 1$ when transaction i takes place after March 26, 2015 *and* the energy efficiency rating of the underlying property is below 39; $X_i = 0$ otherwise. The parameter $\rho_{\text{Regulation}}$ captures the causal effect of treatment. The model is derived from the first principles in Section IA.4.2 of the Internet Appendix.

We estimate Equation (11) on a sample of private-rental properties rated between 1 and 68 that were transacted between January 1, 2011 and December 31, 2019. Excluding owner-occupied dwellings and private-rental properties rated 69 or above helps us homogenise our sample and strengthen the parallel trends assumption.[25] Restricting the duration helps us avoid the potential confounding impacts of the 2008 Global Financial Crisis and the 2020 Covid-19 pandemic. We find that, contrary to our expectations, $\hat{\rho}_{\text{Regulation}}$ is positive (1.45%) and statistically significant (t-statistic = 3.54). The inclusion of higher-rated properties and

[24]This is known as the "counterfactual trends" or "parallel trends" assumption.

[25] In particular, the UK Government announced the Clean Growth Strategy on 12 October 2017, which was not a regulatory announcement, but outlined the government's agenda to upgrade as many dwellings as possible to a rating 69 or above where practical, cost-effective, and affordable. The manifesto was criticised for being vague (see https://publications.parliament.uk/pa/cm201719/cmselect/cmbeis/1730/173005.htm). However, its announcement may lead to short-term violations of the counterfactual trends assumption owing to properties rated 69 or above transacting at (an additional) premium. Section IA.4 of the Internet Appendix shows that controlling for a fixed effect for this manifesto or including higher-rated properties does not impact our results from estimating Equation (11).

the expansion or contraction of the sample duration do not result in a negative and significant treatment effect. The contrary results raise concerns about potential model misspecification.

Thus, we use a *regression discontinuity design* to validate our findings. Lee and Lemieux (2010) remark that regression discontinuity designs require milder assumptions compared to those needed for difference in differences. Regression discontinuity is used to establish causal inferences in settings where the treatment is a deterministic and discontinuous function of a covariate and agents have an imprecise control over which side of the treatment cutoff they will land on. In such a situation, we can think of the assignment as a randomised experiment and draw causal inferences on the treatment effect. Furthermore, comparisons of average outcomes in a small enough neighbourhood to the left and right of the cutoff should provide an estimate of the treatment effect that does not depend on the correct specification of the model (Angrist and Pischke, 2008). Hence, we can draw more credible causal inferences than the difference in differences approach that requires all trends and interactions to be correctly included in the model.

We now explain how regression discontinuity is applicable in our context. The numerical ratings assigned to dwellings are produced by a government-approved software based on the inputs provided by an accreditor accessor after a comprehensive physical inspection. While the inspection is rigorous and substantiated by photographic documentation, human errors in examining the property or feeding information into the software, and the relative difficulty in accurately ascertaining dwelling characteristics such as age, can result in a property landing on either side of the regulatory threshold. Hence, if we only consider properties with ratings in the proximity of the threshold (that is, 39) and restrict our sample to properties for which an EPC was issued *before* the regulation was introduced (that is, before, the landlords had the incentive to distinguish between dwellings rated above or below 39) but transacted *after* the announcement, we can assume a random assignment. This helps us draw causal inference for whether dwellings affected by the policy transacted at a discount.[26]

[26]The random assignment assumption will not hold for higher-rated dwellings (say, 69 or above). This is because homeowners who own properties with higher energy efficiency ratings may care about the rating of their property, and therefore opt for a rating in a non-random way.

Because the treatment is perfectly known in our context, we estimate a *sharp* regression discontinuity design on a sample of properties with a rating between 33 and 44 issued before the regulatory announcement but transacted after, as follows:

$$\begin{aligned}\log{(P/A)_{ihrt}} = \alpha_r + \delta_t + \xi(\mathrm{S}_{ih} - c) + \mu_t(\mathbb{1}_t \times (\mathrm{S}_{ih} - c)) + \rho X_i \\ + \theta\mathrm{B}_h + \gamma\mathrm{T}_i + \nu\mathrm{IMD}_{rt} + \omega\mathrm{DD}_{rt} + \varepsilon_{ihrt},\end{aligned} \tag{12}$$

where $\mathrm{S}_{ih} - c$ denotes the energy efficiency rating of a property centred around the regulatory threshold $c = 39$, and X_i is an indicator variable for treatment; $X_i = 1$ when $\mathrm{S}_{ih} < c$; $X_i = 0$ otherwise. The parameter ρ captures the causal effect of interest. Other symbols have the same meaning as those in Equation (4) in Section 4.2. Section IA.4.3 of the Internet Appendix derives the model from first principles.

We find that $\hat{\rho}$ is negative (-1.05%), but insignificant (t-statistic $= -0.51$). One concern is the small sample size (4,055 entries) when we impose the additional constraints. However, we find that expanding the neighbourhood around the regulatory threshold does not result in a significant treatment effect. Therefore, we conclude that the regulation did not result in a discount for the affected dwellings that did not upgrade.

Given that a very small proportion of properties that were transacted after the regulation had an energy efficiency rating lower than the regulatory threshold, one potential explanation is that most of these properties qualified for an 'exemption' under the regulatory framework (see Table IA.10 in Section IA.4.4 of the Internet Appendix). For instance, the expected cost of improving the ratings of the affected properties to 39 is £7,862, which is more than two times higher than the £3,500 mark over which landlords can claim a 'High Cost' exemption.[27] Similarly, landlords can also claim an exemption if the required improvements are likely to be detrimental to the property's structural integrity.

[27] We replicate our analysis for the subset of properties for which the expected cost of upgrading to a rating of 39 was less than £3,500 but do not find a negative and significant treatment effect.

7 Conclusion

This manuscript provides definitive and large-scale evidence that homeowners value dwelling energy efficiency in an economically meaningful manner. Our analysis is facilitated by the compilation of a comprehensive dataset containing more than seventy percent of residential real estate transactions recorded in the United Kingdom between 2010 and 2020. Through a simple valuation approach, we recover the discount rates that homeowners use to appraise dwelling sustainability, and show that the market is willing to accept lower returns for greener dwellings. Lastly, we show how regulatory interventions indirectly contributed to an increase in the demand for greener dwellings.

We contribute to extant literature in three ways. First, by developing a custom algorithm that uniquely matches dwellings across different sources of data, we overcome a hiatus which has precluded a detailed examination of how dwelling energy efficiency is priced in residential real estate markets. Second, we show that homeowners "care" about the environment more broadly, and not only when their dwellings are subject to disaster-related risks. Finally, our analysis provides more direct measures for rates used to discount investments in sustainable development and climate change mitigation. A key distinguishing feature of this manuscript is the measurement of the cross-sectional heterogeneity in preferences.

References

Amecke, Hermann, 2012, The impact of energy performance certificates: A survey of German home owners, *Energy Policy* 46, 4–14.

Angrist, Joshua D., and Jörn-Steffen Pischke, 2008, *Mostly harmless econometrics* (Princeton University Press).

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis, 2020, Does climate change affect real estate prices? Only if you believe in it, *The Review of Financial Studies* 33, 1256–1295.

Baranzini, Andrea, José Ramirez, Caroline Schaerer, and Philippe Thalmann, 2008, *Hedonic methods in housing markets: Pricing environmental amenities and segregation* (Springer Science & Business Media).

Berkouwer, Susanna B., and Joshua T. Dean, 2022, Credit, attention, and externalities in the adoption of energy efficient technologies by low-income households, *American Economic Review* 112, 3291–3330.

Bernstein, Asaf, Matthew T. Gustafson, and Ryan Lewis, 2019, Disaster on the horizon: The price effect of sea level rise, *Journal of Financial Economics* 134, 253–272.

Brounen, Dirk, and Nils Kok, 2011, On the economics of energy labels in the housing market, *Journal of Environmental Economics and Management* 62, 166–179.

Cajias, Marcelo, Franz Fuerst, and Sven Bienert, 2019, Tearing down the information barrier: The price impacts of energy efficiency ratings for buildings in the German rental market, *Energy Research & Social Science* 47, 177–191.

Cajias, Marcelo, and Daniel Piazolo, 2013, Green performs better: Energy efficiency and financial return on buildings, *Journal of Corporate Real Estate* .

Cerin, Pontus, Lars G. Hassel, and Natalia Semenova, 2014, Energy performance and housing prices, *Sustainable Development* 22, 404–419.

Clara, Nuno, Joao F. Cocco, S Lakshmi Naaraayanan, and Varun Sharma, 2024, Investments that make our homes greener: The role of regulation, *Available at SSRN 4009054* .

Davis, Lucas W., 2012, Evaluating the slow adoption of energy efficient investments: Are renters less likely to have energy efficient appliances?, in Don Fullerton and Catherine Wolfram, (eds.) *The Design and Implementation of US Climate Policy*, 301–316 (University of Chicago Press).

Davis, Peadar T., John A. McCord, Michael McCord, and Martin Haran, 2015, Modelling the effect of energy performance certificate rating on property value in the Belfast housing market, *International Journal of Housing Markets and Analysis* .

Fuerst, Franz, Michel Ferreira Cardia Haddad, and Hassan Adan, 2020, Is there an economic case for energy-efficient dwellings in the UK private rental market?, *Journal of Cleaner Production* 245, 118642.

Fuerst, Franz, Pat McAllister, Anupam Nanda, and Peter Wyatt, 2016, Energy performance ratings and house prices in Wales: An empirical study, *Energy Policy* 92, 20–33.

Fuerst, Franz, Patrick McAllister, Anupam Nanda, and Peter Wyatt, 2015, Variations in the implicit pricing of energy performance by dwelling type and tenure: A study of Wales, *Available at SSRN 2633539* .

Gerarden, Todd D., Richard G. Newell, and Robert N. Stavins, 2017, Assessing the energy-efficiency gap, *Journal of Economic Literature* 55, 1486–1525.

Giglio, Stefano, Matteo Maggiori, Krishna Rao, Johannes Stroebel, and Andreas Weber, 2021, Climate change and long-run discount rates: Evidence from real estate, *The Review of Financial Studies* 34, 3527–3571.

Giglio, Stefano, Matteo Maggiori, and Johannes Stroebel, 2015, Very long-run discount rates, *The Quarterly Journal of Economics* 130, 1–53.

Gordon, Myron J., 1982, *The Investment, Financing, and Valuation of the Corporation* (Greenwood Press, Westport, CT).

Groom, Ben, and David Maddison, 2019, New estimates of the elasticity of marginal utility for the UK, *Environmental and Resource Economics* 72, 1155–1182.

Högberg, Lovisa, 2013, The impact of energy performance on single-family home selling prices in Sweden, *Journal of European Real Estate Research* .

Hyland, Marie, Ronan C. Lyons, and Sen Lyons, 2013, The value of domestic building energy efficiency evidence from Ireland, *Energy Economics* 40, 943–952.

Intergovernmental Panel on Climate Change, 2022, Sixth assessment report of the intergovernmental panel on climate change .

International Energy Agency, 2021, Net zero by 2050: A roadmap for the global energy sector.

Iwata, Shinichiro, and Hisaki Yamaga, 2008, Rental externality, tenure security, and housing quality, *Journal of Housing Economics* 17, 201–211.

Jaffe, Adam, Robert Stavins, and Cutler Cleveland, 2004, *Economics of Energy Efficiency*, 79–90 (Elsevier).

Jensen, Ole Michael, Anders Rhiger Hansen, and Jesper Kragh, 2016, Market response to the public display of energy performance rating at property sales, *Energy Policy* 93, 229–235.

Kaplow, Louis, Elisabeth Moyer, and David Weisbach, 2010, The social evaluation of intergenerational policies and its application to integrated assessment models of climate change, *The B.E. Journal of Economic Analysis & Policy* 10, 1–34.

Lee, David S., and Thomas Lemieux, 2010, Regression discontinuity designs in economics, *Journal of Economic Literature* 48, 281–355.

Murfin, Justin, and Matthew Spiegel, 2020, Is the risk of sea level rise capitalized in residential real estate?, *The Review of Financial Studies* 33, 1217–1255.

National Audit Office, 2016, Green deal and energy company obligation, Technical report.

Nordhaus, William D., 2007, A review of the stern review on the economics of climate change, *Journal of Economic Literature* 45, 686–702.

Nordhaus, William D., 2013, Discounting and the value of time, in *The Climate Casino: Risk, Uncertainty, and Economics for a Warming World* (Yale University Press).

Pástor, L'uboš, Robert F Stambaugh, and Lucian A Taylor, 2021, Sustainable investing in equilibrium, *Journal of financial economics* 142, 550–571.

Ramsey, Frank Plumpton, 1928, A mathematical theory of saving, *The Economic Journal* 38, 543–559.

Rehdanz, Katrin, 2007, Determinants of residential space heating expenditures in Germany, *Energy Economics* 29, 167–182.

Schneider, Maik, Christian Traeger, and Ralph Winkler, 2012, Trading off generations: Equity, discounting, and climate change, *European Economic Review* 56, 1621–1644.

Stern, Nicholas H., 2007, *The economics of climate change: The Stern review* (Cambridge University Press).

UK Government, 2007, The energy performance of buildings (Certificates and inspections) (England and Wales) regulations 2007.

UK Government, 2017, Domestic private rented property: Minimum energy efficiency standard - landlord guidance .

UK Government, 2022a, English Housing Survey: Headline report, 2020-21 .

UK Government, 2022b, The Green Book (2022) .

Zhuang, Juzhong, Zhihong Liang, Tun Lin, and Franklin De Guzman, 2007, Theory and practice in the choice of social discount rate for cost-benefit analysis: A survey, Technical report, ERD Working Paper Series.

Internet Appendix

to “Green Expectations: Climate Change and Homeowner Valuation of Dwelling Sustainability”

IA.1 Supplement to data

This appendix supplements Section 2 in the main body of the manuscript.

IA.1.1 Problems with Levenshtein distance

As discussed in Section 2.1.2, in order to investigate the relationship between property values and energy profiles, we must link each transaction recorded in the HM Land Registry with a valid EPC through address matching. Unfortunately, addresses are not entered consistently within and between datasets. For example, the address `FLAT 42, 16A BROADWAY STREET, 413` may also be recorded as `42 BROADWAY STREET, 16A 413`. One method to link addresses is to use *fuzzy* matching techniques such as the Levenshtein distance, which computes the minimum number of single-character edits (insertions, deletions, or substitutions) required to change one word into the other.

Although programming packages are readily available for implementing such inexact techniques, it is unclear what the correct threshold to set is in order to maximise the ratio of correct to incorrect matches in our use case. For example, consider housing units within the same building: '`FLAT 42A, BROADWAY STREET`', '`FLAT 42B, BROADWAY STREET`, '`FLAT 42C, BROADWAY STREET`', and so on. The addresses of the housing units only differ by a single letter. The minimum threshold that can be set for an algorithm implementing Levenshtein distance to allow for inexact matches is also one. Therefore, all housing units in this building will be identified as the same across and within datasets, as it takes a single substitution to convert one of these addresses to the other.

In addition to being computationally intensive, these techniques are also sensitive to the manner in which addresses are formatted. For instance, `42 BROADWAY STREET, 16B 413` would be considered closer to `42 BROADWAY STREET, 16A 413` than `FLAT 42, 16A BROADWAY STREET, 413`, as deleting `FLAT` requires more operations than replacing `B` with `A`. Furthermore, we find that in several instances, parts of addresses are repeated across fields. For example, `42 BROADWAY STREET, 413` may also be stored as `42 BROADWAY, BROADWAY STREET`

`413`. Deleting the word `BROADWAY` will take eight operations, and therefore, the two addresses will be treated as different by the an algorithm with a threshold less than eight. On the other hand, any algorithm with such high threshold will yield a large number of inexact matches. Given the heterogenous nature of real estate data, inexact matches may distort results substantially.

IA.1.2 Exact address matching algorithm

We develop a custom algorithm that produces *exact* matches, but results in a smaller dataset post-compilation. The procedure is relatively straightforward, but requires careful investigation of how the data is stored and the potential errors that can arise when attempting to match entries. We provide a step-by-step outline here.

Addresses in both Price Paid Data and the Energy Performance of Buildings Register are split across multiple subfields. For instance, the Price Paid Data records `PAON` (building number), `SOAN` (apartment number if a property contains multiple housing units), and `STREET`. The Energy Performance of Buildings Register splits addresses into `ADDRESS1`, `ADDRESS2`, and `ADDRESS3`. Upon manual inspection, we find that the manner in which addresses are recorded in the Energy Performance of Buildings Register presents two challenges. First, for certain local authorities, locational identifiers (such as building names) present in `ADDRESS2` are repeated in `ADDRESS1`. We correct for these duplications. Second, `ADDRESS2` often contains the name of the post-town of the property, which is supposed to be in a separate subfield and is not required for matching addresses, as we have information on postcodes, which are exact and more granular than post-towns. We further find that the post-towns mentioned in `ADDRESS2` are often incorrect. This we purge `ADDRESS2` of all post-town names available in the dataset.

In addition, we find that the addresses in the Energy Performance of Buildings Register may not always uniquely identify a property. This typically occurs when two housing units within the same building omit the Secondary Addressable Object Name (SAON) from their respective addresses. For instance, both `FLAT 12, 20 BROADWAY STREET` and `FLAT 14, 20`

`BROADWAY STREET` may be recorded as `20 BROADWAY STREET`. To ensure that each property in the mapped (or linked) dataset is uniquely identified, we remove entries with *address keys* that map to more than one *Building Reference Number* (BRN) in the Energy Performance of Buildings Register, as BRNs are uniquely assigned to each property even if the address recorded in the database is not. Out of 17,827,487 EPCs issued between January 1, 2010 and December 31, 2020, there are 14,807,313 unique address keys but 14,960,081 BRNs.

Then, we start by concatenating the address subfields in each dataset in descending order of granularity. Thus, apartment numbers come before property numbers, which in turn come before the street address. We convert the concatenated address to uppercase letters and remove keywords that are commonly omitted between one address and another. These are `FLAT`, `APARTMENT`, and `BUILDING`.[28] Therefore `FLAT 42, 16A BROADWAY STREET, 413` becomes `42, 16A BROADWAY STREET, 413`. We then filter out non-alphanumeric characters (i.e., spaces, punctuations, and special characters are removed) and reorganise the address so that numbers (both with and without an alphabetical qualifier such as `16` or `16A`) are moved in front of words. These operations convert `42, 16A BROADWAY STREET, 413` to `4216A413BROADWAYSTREET`. Lastly, we add the formatted text to the postcode of the building producing a unique *address key*, e.g., `NW14SA4216A413BROADWAYSTREET` where `NW1 4SA` is the building's postcode. The main limitation of our algorithm is that we are unable to account for spelling mistakes in addresses.

The HM Land Registry records 9,808,400 transactions between January 1, 2010 and December 31, 2020. Of these, 9,692,971 transactions take place in postcodes for which we have entries in the Energy Performance of Buildings Register. Of these, we are able to uniquely map 7,239,549 transactions (73.8% of 9,808,400) using our exact-matching technique.

We could potentially consider using Levenshtein distance on the alphanumeric characters after the non-alphanumeric characters are moved to the front. This would make the algorithm computationally (and memory) intensive, as within each postcode, we will have to compare

[28] The algorithm can be potentially improved even further by identifying more such keywords.

all addresses with one another. However the main deterrent is that once we process the data and drop records with missing values for the variables used in our analysis, we are only left with 5,451,054 out of 7,239,549 entries. Thus, attempting to increase the number of records matched may only result in a marginal increase in the final regression sample, and therefore, may not justify the increased computational complexity and a potential for inexact matches.

IA.1.3 Detailed notes of feature selection and formatting

We are able to uniquely map 7,239,549 transaction entries using our exact matching algorithm. We can classify the set of features in the *mapped sample* into two types: (i) those required to construct dependent variables (i.e., price and total floor area) and independent variables whose coefficients we are primarily interested in (i.e., energy efficiency scores), and (ii) those that act as hedonic controls (e.g., built form, transaction type, age) or facilitate investigative analysis (e.g., utility costs and environmental impact). Since, entries in the mapped dataset are incomplete and contain `null` values, we must trade-off the number of type (ii) features with the total number of entries in the dataset. Note that entries for which a type (i) has a `null` value *must* be removed for analysis, and therefore do not present a trade-off. There is no fixed rule on how to accomplish this. Nonetheless we are able to retain all features that are of first order importance; and are enumerated in Table IA.1.

Thereafter we format (or clean) the mapped dataset feature-by-feature. This section walks the reader through feature-by-feature implementation details. The compiled dataset post-processing contains 7,022,645 entries, that is, we loose roughly 1% of 7,239,549 entries from wrangling, formatting, and cleaning. Table IA.2 provides a quick summary of the key operations in the order in which they are carried out.

Energy Ratings. We filter out entries for which the Potential Energy Score is less than that of the Current Energy Score. This results in a loss of 890 entries. We cap the Potential

Table IA.1: Selected features from PPD and EPBR

Category	Feature	Measurement
General	Price[1]	GBP, e.g., 102500, 45000
	Transaction Year[1]	Year, e.g., 2008, 2019
Energy Ratings	Current Energy Label[2]	Alphabetical label from G to A
	Potential Energy Label[2]	
	Current Energy Score[2]	Numerical score from 1 to 100
	Potential Energy Score[2]	
Building Properties	Total Floor Area	Squared meters, e.g., 60, 85
	Property Type	Categorical, e.g., House, Flat
	Built Form	Categorical, e.g., Detached, Mid-Terrace
	Habitable Rooms	Integer, e.g., 2, 3, 4
	Newly Built[1]	Categorical, either Yes or No
	Construction Age Band	Categorical, e.g., 1900-1929, 1930-1949
	Glazed Area	Categorical, e.g., Normal, More than Typ.
	Multi-Glaze Proportion	Percentage value from 0 to 100
Transaction Characteristics	Tenure	Categorical, e.g., Owner-occupied, Rental
	Transaction Type	Categorical, e.g., Marketed Sale
	Ownership[1]	Categorical, either Freehold or Leasehold
Environmental Metrics	Current Environmental Impact	Numerical score from 0-100 based on
	Potential Environmental Impact	carbon emissions (higher is better)
	Current Energy Consumption	Annual energy consumption measured in
	Potential Energy Consumption	kWh per squared meter
	Current Carbon Emissions	Tonnes per year
	Potential Carbon Emissions	
Utility Costs	Current Lighting Cost	Annual cost in GBP
	Potential Lighting Cost	
	Current Heating Cost	
	Potential Heating Cost	
	Current Hot Water Cost	
	Potential Hot Water Cost	
Locational Identifiers	Postcode	Alphanumeric, e.g., NW1 4SA, HA9 0QE
	Local Authority	Alphabetical, e.g., Camden, Oxford
	Local Authority Code	Alphanumeric, e.g., E06000042
	Constituency Code	Alphanumeric, e.g., E14000822

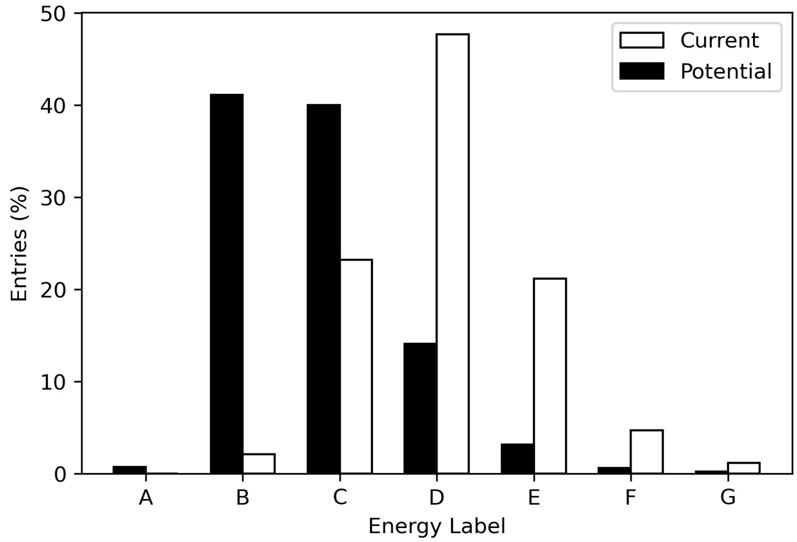
1. Features that belong to the Price Paid Data.
2. Current (Potential) Energy Rating (Efficiency) has been renamed to Current (Potential) Energy Label (Score) to make it clearer to the reader whether the energy rating being referred to is a numerical "score" or an alphabetical "label".

Table IA.2: Formatting features

Category	Operation	Entries
Mapped Data		**7,239,549**
Energy Ratings	Ensure that current energy ratings are less than potential.	(890)
	Cap current and potential energy scores to 100.	—
Building Characteristics	Total floor area is between 20 and 400 square meters.	(23,637)
	Property type is not `Park Home`.	(22)
	Property has 1 to 12 habitable rooms.	(3,023)
	Collapse construction age bands post-2007 into one class.	—
	Subsume `Much More (Less) Than Typical` glazed area into `More (Less) Than Typical` categories.	—
	Collapse multi-glaze area into a categorical variables with three classes: High (≥ 66.6), Low(≤ 33.3), and Medium.	—
	Floor (Cap) low energy lighting proportion at 0 (100).	—
Transaction Characteristics	Remove entries for which tenure is unknown.	(10,669)
	Cluster categories with few or related entries.	—
Price	Restrict entries with price per unit area within the 0.25% and 99.75% quantiles.	(35,975)
Environmental Metrics	For current (potential) environmental impact, restrict entries within the 0.01% and 99.99% quantiles. Divide current (potential) carbon emission and energy consumption metrics by the total floor area and restrict the sample to 99.98% quantile range. Floor (or cap) aforementioned metrics between 0 and 100.	(2,249)
	Remove entries for which potential environmental impact is greater than current, and for which current carbon emissions and energy consumption are greater than potential.	(41,179)
Utility Costs	Restrict current (potential) heating, lighting and hot water costs to the 99.98% quantile range.	(3,480)
	Remove entries for which current utility costs are less than potential costs with a 2.5% tolerance. Format entries inside the tolerance range so that current equals potential.	(95,780)
Formatted Data		**7,022,645**

Operations are listed in the order in which they are carried out. Because formatting Price, Environmental Metrics, and Utility Costs involve operations that eliminate entries outside a given quantile range, they are carried out at the end to minimise the loss of entries.

Figure IA.1: Distribution of EPC labels



This figure shows the distribution (y-axis) of the Current and Potential energy efficiency labels (x-axis) in the compiled data using white and black bars, respectively.

Energy Scores to 100. Figure IA.1 shows the distribution of Current and Potential Energy Labels.[29]

Building Characteristics. We restrict ourselves to properties with a Total Floor Area between the 0.01 (34 m^2) and 0.99 (243 m^2) percentiles, which eliminates 23,637 observations. We remove 22 properties with Property Type as "Park Home". We remove 3,023 entries with 0 or more than 12 habitable rooms. In instances where two or more Construction Age Bands are not mutually exclusive, we club them together. For example, we combine "2007 onwards", "2007-2011", and "2012 onwards" into a single category, "2007 onwards". We also rename categories for various categorical variables to make them more readable. For example, "Y"("N") values in feature New were changed to "Yes"("No") and the prefix from Construction Age Bands was removed, rendering "England and Wales: 1900-1929" to "1900-1929".

For Glazed Area, we subsume the 88 "Much Less Than Typical" and 1731 "Much More Than Typical" values into "Less Than Typical" and "More Than Typical" respectively.

[29]The figures shown throughout Section 2 are based on the final dataset produced post-processing, and therefore, provide an accurate description of the final dataset used for analysis.

Given that the Multi-Glaze Proportion for more than 75% of properties is 100%, we convert the feature into a categorical variable, with "High" ($\geq$66.5%), "Low" ($\leq$33.3%), and "Medium" categories. Finally, we cap Low-Energy Lighting Proportion to 100.

Transaction Characteristics. The same category in Tenure is stored in different formats; we clean these category names to obtain three classifications, "Owner Occupied", "Rental (Social)", and "Rental (Private)". We drop 10,669 entries for which Tenure can not be determined. Several categories in Transaction Type have very few entries, or are closely related to one another. We combine "Eco" and "FiT" assessments into a single category; all categories related to "Rental" properties are subsumed into one; "Stock Condition Survey" and other miscellaneous categories are classified as "Other".

Note: When formatting the dataset based on price, cost and energy measures, as described next, we divide them by the Total Floor Area to enable comparisons between properties. We also filter the dataset based on such features at the end as these filters involve elimination of extreme values based on percentiles, which would lead to a higher loss of entries if carried out before the formatting steps carried out in the previous sections.

Price. We remove properties with price per unit area less than 0.0001 or more than 0.9999 percentiles, resulting in a loss of 35,975 entries.

Environmental Metrics. We remove entries outside the 0.0001 and 0.9999 percentile range for Current Environmental Impact, Carbon Emissions per unit area, and Energy Consumption per unit area, resulting in a loss of 2,249 entries. We also filter out properties for which Potential Carbon Emissions and Energy Consumption values are lower and Current ones, and for which the Current Environmental Impact score is higher than the Potential score, resulting in a further loss of 41,179 entries.

Utility Costs. We start by removing properties for which Current Lighting, Heating, and Hot Water Cost is outside the 0.0001 and 0.9999 percentile range, loosing 3,480 entries. Ideally, we would like to filter out all entries where Potential costs are higher than the Current ones; however, doing so results in a loss of roughly 25% of the dataset. Therefore, we introduce a small *threshold* set to 1/20th of the median of cost per unit area. Entries for which Current costs are less than Potential costs minus the threshold are removed. For entries that are within this threshold and have Potential costs greater than the Current ones, we set the Potential costs equal to the Current costs.

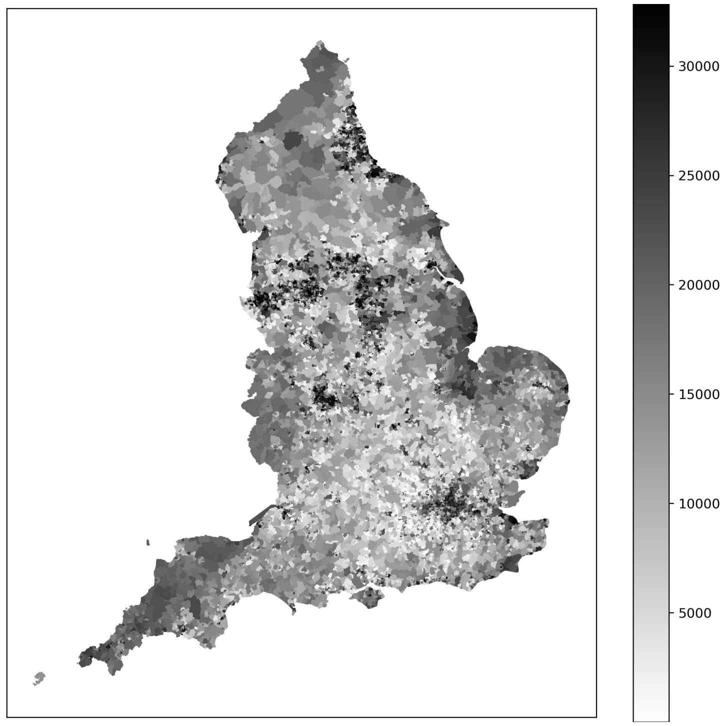
For example, we calculate the median of Current Heating Cost per unit area and divide it by 20 to obtain the threshold τ. If Current Heating Cost per unit area is less than Potential Heating Cost per unit area minus τ, we remove the entry. For the remaining entries, if the Potential Heating Cost is greater than the Current Heating Cost, we set it to the Current value. We repeat this process for Lighting and Hot Water costs, resulting in a total loss of 95,780 entries.

IA.1.4 Compiling English indices of multiple deprivation

The English Indices of Multiple Deprivation (IMD) are available for the years 2007, 2010, 2015, and 2019. There are seven component indices – Income, Employment, Education, Health Deprivation, Crime, Housing Barrier, and Living Environment – which are combined to obtain a composite IMD index. There are four considerations in compiling these indices for analysis. First, the format in which the indices are recorded is inconsistent across reports. Therefore, we manually reorganise the indices into tabulated files in a consistent format so that they can be processed using a script.

The second consideration is that the 2007 and 2010 IMD are reported for the 32,482 LSOA regions constructed in 2001, whereas the 2015 and 2019 IMD are reported for the 32,844 LSOA regions constructed in 2011. We use the LSOA 2001 to LSOA 2011 Lookup table published by the Office of National Statistics to link the two. However, LSOA 2001 to LSOA 2011 conversions are not one-to-one. There are splits (S), merges (M), exact matches (U), and best fits (X). Therefore, we group by LSOA 2011 and take an average. If an LSOA 2001 was split into two zones in 2011, then both zones will have the same 2001 entries, and

Figure IA.2: IMD ranks



This figure illustrates the distribution of ranks based on the composite IMD index through a heatmap. Ranks are normalised between 0 and 100 by dividing 2007 and 2010 ranks by 32,482, and 2015 and 2019 ranks by 32,844.

taking the average does not impact 2001 scores. If 2001 areas were merged into a 2011 area, then this operation takes an average.[30]

The third consideration is to select one of two formats in which the indices are reported: *scores* or *ranks*. We use ranks in our analysis as they involve fewer mathematical transformations in their construction, are less polarised, and in general, the recommended measure for analysis in government documentation and reports. Figure IA.2 illustrates the distribution of ranks based on the composite index through a heatmap. We normalise the ranks from 0 to 100 by dividing 2007 and 2010 ranks by 32,482, and 2015 and 2019 ranks by 32,844.[31]

[30] Note that taking naive averages is not completely accurate, as ideally, we should weight the average by population, number of houses, or the area of the region.

[31] We find that using scores instead of ranks, using non-normalised ranks, or sorting ranks into 100 quantiles does not impact our regression estimates for energy premium in Section 3.

Finally, we must interpolate indices for those years between 2010 and 2020 for which we do not have an IMD report. Two natural candidates are *linear interpolation (and extrapolation)* and *stepwise assignment*. The former would be a good approach if the direction of change in ranks from one report to another was somewhat predictable. However, we find that this is not the case: ranks for 22.9% of LSOAs continued to increase from 2010 to 2015 and from 2015 to 2019; 21.36% of LSOAs continued to decrease; whereas ranks for 27.04% of LSOAs increased from 2010 to 2015, but decreased from 2015 to 2019; and those for 23.16% of LSOA decreased from 2010 to 2015 but increased from 2015 to 2019. We therefore opt for a stepwise approach, and for each year, assign the rank corresponding to the most recent IMD report. For example, the ranks for 2018 are taken from the 2015 IMD report, and those for 2020 are taken from the 2019 IMD report.

IA.1.5 Constructing degree days measure

For each of one the 10,432 5×5km grids represented by coordinates, we work with average monthly temperature values recorded by the Meteorological Office from January 2007 to December 2020. We calculate degree days (DD^o) for month m in year t for grid g as:

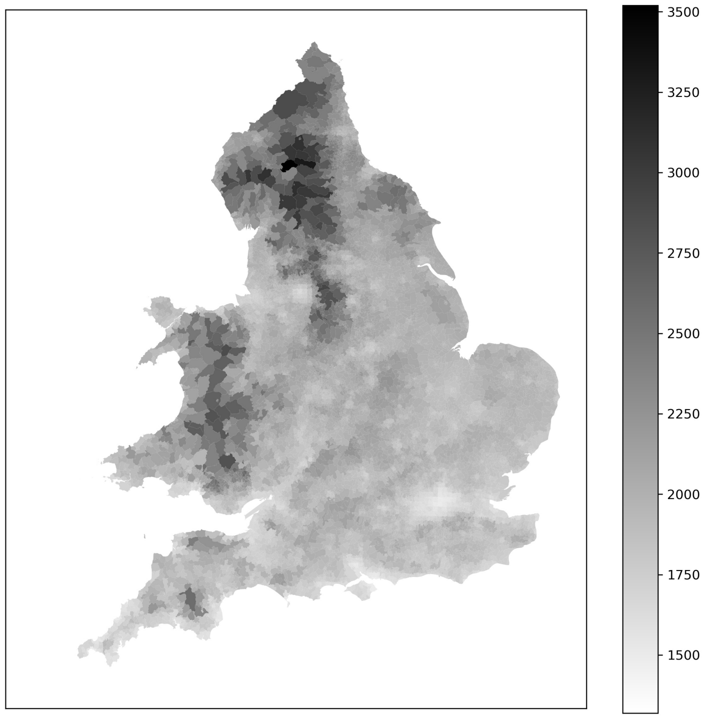
$$DD^o_{gmt} = \max(0, B - T_{gmt}) \times N_m,$$

where B is a pre-specified baseline temperature value, typically set to 15.5 °C, T_{gmt} is the average temperature recorded for month m in year t for grid g, and N_m is the number of days in the month. For each year, we then sum over the monthly degree days to obtain the annual degree day measure $DD^o_{gt} = \sum_m DD^o_{gmt}$.[32] The higher the degree days, the colder the climate, and the more the heating requirements for a given building at a specific location.

It is also useful to think about how degree days would factor into a property transaction. The buyer and seller cannot know the aggregate degree days for the year in which the

[32] Typically, these calculations are done on a daily basis, or even an intraday basis, and then aggregated to monthly or annual measures. By using monthly average temperature values instead, we will underestimate degree days, since if the mean temperature of the month is greater than 15.5 °C, the HDD for the month will be 0, but if we used daily data, this might not be the case. Because downloading and processing daily data is significantly more computationally intensive, we opt for the less granular approach.

Figure IA.3: Average degree days



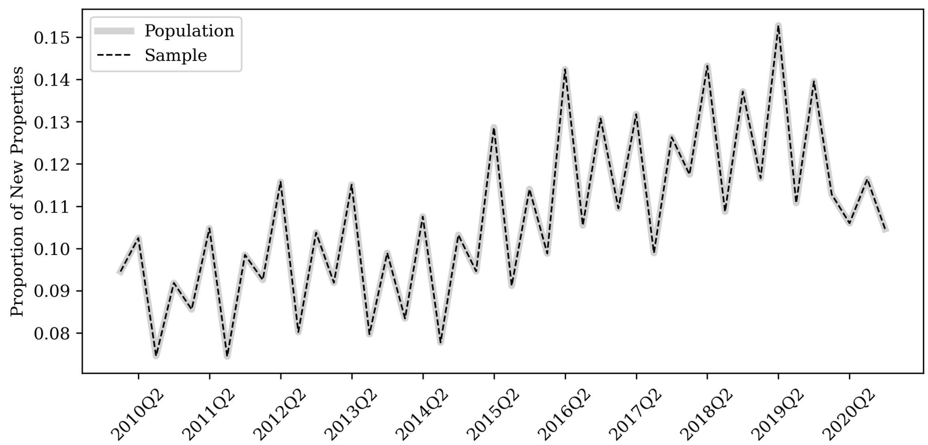
This figure illustrates the average of degree days measure over the analysis period (2008 to 2021) for each LSOA 2011 in the United Kingdom.

transaction occurs. Additionally, an unusually hot or cold year is unlikely to factor into property valuation. Therefore, for each year from 2010 to 2020, we use the average of degree days value taken over the preceding three years, denoted by $\overline{DD^o}_{gt} = (1/3)\sum_{k=t-3}^{t-1} DD^o{}_{gk}$. For example, we use the average of degree days from years 2017 to 2019 for 2020, and from 2007 to 2009 for 2010.

Because we have degree days for grids represented by a unique set of coordinates, we use the LSOA 2011 Boundaries dataset published by the Office of National Statistics to extract the representative coordinate for each of the 32,844 LSOA 2011 and assign to them the degree days values for years 2008 through 2021 for the grid that is closest in (Euclidean) distance to each LSOA.[33] Figure IA.3 illustrates the average of degree days over the analysis period (2008 to 2021) for each LSOA 2011 in the United Kingdom.

[33]Typically, Euclidean distance must be avoided in geospatial distance measurements as it does not take into account the curvature of Earth, but since we are interested in the closest match (which is less than 5km here), using Euclidean distance will produce reasonably accurate matches.

Figure IA.4: Proportion of new dwellings sampled



This figure shows the proportion of new dwellings (y-axis) sampled from the PPD in each quarter (x-axis). The thick grey line represents the proportion of properties that are marked new in the PPD, and the dashed black line represents the proportion of properties that are marked new in the regression sample.

Lastly, because degree days computed in this manner depend on the frequency at which temperature observations are recorded, the unit of measurement is not a "day" and the values should be interpreted *relative* to each other. Therefore, we use min-max normalisation to rescale the values between 0 and 100 as follows:

$$DD_{rt} = 100 \times \frac{\overline{DD^o}_{rt} - \min_{rt} \overline{DD^o}_{rt}}{\max_{rt} \overline{DD^o}_{rt} - \min_{rt} \overline{DD^o}_{rt}},$$

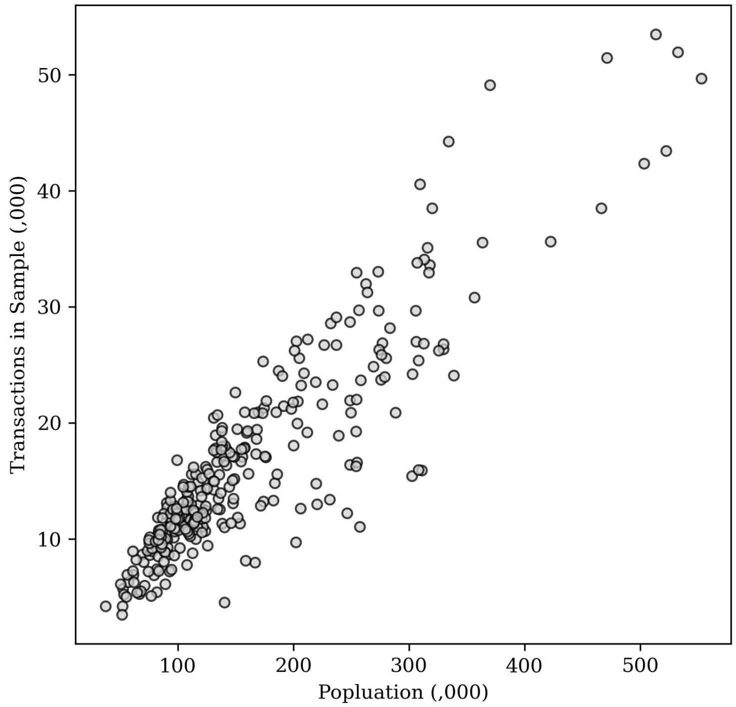
where DD_{rt} is the final degree days measure for region r in year t that we use in our analysis.

IA.1.6 Sample properties

This section provides supplementary figures and tables related to the discussion on sample properties in Section 2.2.

Figure IA.4 reports the number of new dwellings sampled from the PPD in each quarter. This figure shows the proportion of new dwellings (y-axis) sampled from the PPD in each quarter (x-axis). The thick grey line represents the proportion of properties that are marked new in the PPD, and the dashed black line represents the proportion of properties that are marked new in the regression sample. The grey and the black lines overlap, indicating that new dwellings are sampled proportionately from the PPD.

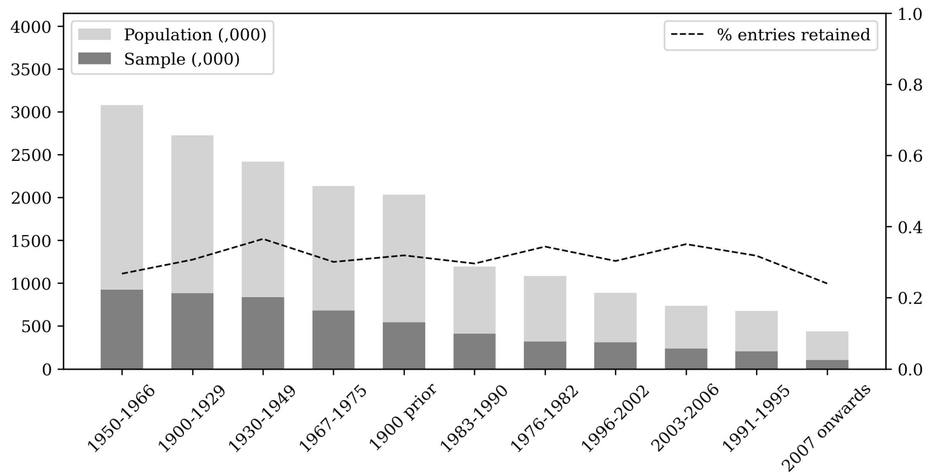
Figure IA.5: Transactions relative to population



The figure shows the total number of transactions sampled from each local authority against its population. Each circular marker corresponds to one of the 341 local authorities in the Energy Performance of Buildings Register. The x-axis corresponds to the population in each local authority, obtained from the 2011 Rural Urban Classification data published by the Department for Environment, Food & Rural Affairs. The y-axis corresponds to the number of transactions sampled from each local authority. The axes are scaled so that they differ only by an order of magnitude.

Figure IA.5 shows the total number of transactions sampled from each local authority against its population. Each circular marker corresponds to one of the 341 local authorities in the Energy Performance of Buildings Register. The x-axis corresponds to the population in each local authority, obtained from the 2011 Rural Urban Classification data published by the Department for Environment, Food & Rural Affairs. The y-axis corresponds to the number of transactions sampled from each local authority. The axes are scaled so that they differ only by an order of magnitude. The circular markers are approximately aligned along a 45-degree diagonal, indicating that the number of transactions sampled for each local authority is roughly proportional to its population.

Figure IA.6: Entries sampled per construction period



The x-axis marks the various Construction Age Band categories in the Energy Performance of Buildings Register. For each age band, the height of the light grey columns corresponds to the primary (left) y-axis, and represents the number of entries present in the dataset, in thousands. The dark grey columns represent how many entries, in thousands, were retained in the regression sample. The black dashed line corresponds to the secondary (left) y-axis and represents the proportion of entries sampled from the Energy Performance of Buildings Register for each age band.

Figure IA.6 shows the composition of the properties belonging to different construction periods. The x-axis demarcates the various Construction Age Band categories in the Energy Performance of Buildings Register. For each Construction Age Band, the height of the light grey columns corresponds to the primary (left) y-axis, and represents the number of entries present in the dataset, in thousands. The dark grey columns represent how many entries, in thousands, were retained in the regression sample. The black dashed line corresponds to the secondary (left) y-axis and represents the proportion of entries sampled from the Energy Performance of Buildings Register for each band. We observe that the proportions of transactions sampled across different construction bands are comparable.

Finally, Table IA.3 reports the composition of properties with multiple transactions in the PPD and the regression sample. The column titled "Transactions" reports the number of transactions observed for a given Address Key (see Section IA.1.2) over the duration of our sample. The columns titled "Address Key" and "Proportion" under the heading

Table IA.3: Sampling dwellings with multiple transactions

	Populaton		Sample	
Transactions	Address Key	Proportion(%)	Address Key	Proportion(%)
1	6,355,649	79.96	4,663,761	80.83
2	1,381,325	17.38	970,760	16.83
3	190,622	2.40	124,103	2.15
4	18,398	0.23	10,107	0.18
5	1,991	0.03	734	0.01

The column titled "Transactions" reports the number of transactions observed for a given Address Key (see Section IA.1.2) over the duration of our sample. The columns titled "Address Key" and "Proportion" under the heading "Population" represent the number and the proportion of properties in the PPD, respectively, with the number of transactions corresponding to the column titled "Transactions". The columns under the heading "Sample" replicate the analysis for the regression sample.

"Population" represent the number and the proportion of properties in the PPD, respectively, with the number of transactions corresponding to the column titled "Transactions". The columns under the heading "Sample" replicate the analysis for the regression sample. The table shows that dwellings with multiple transactions are sampled proportionately from the population data.

IA.2 Supplement to measuring energy premium

This appendix supplements Section 3 in the main body of the manuscript.

IA.2.1 Sample certificate

This section shows a sample Energy Performance Certificate (EPC) provided by the UK Government, accessible at https://assets.publishing.service.gov.uk/media/5a748d20ed915d0e8bf19346/1790388.pdf. A schematic diagram of the lead page of the sample certificate is shown in Figure 7 of Section 3.

Energy Performance Certificate (EPC)

© Crown copyright 2009

17 Any Street, District, Any Town, B5 5XX

Dwelling type:	Detached house	**Reference number:**	0919-9628-8430-2785-5996
Date of assessment:	15 August 2011	**Type of assessment:**	RdSAP, existing dwelling
Date of certificate:	13 March 2012	**Total floor area:**	165 m²

Use this document to:

- Compare current ratings of properties to see which properties are more energy efficient
- Find out how you can save energy and money by installing improvement measures

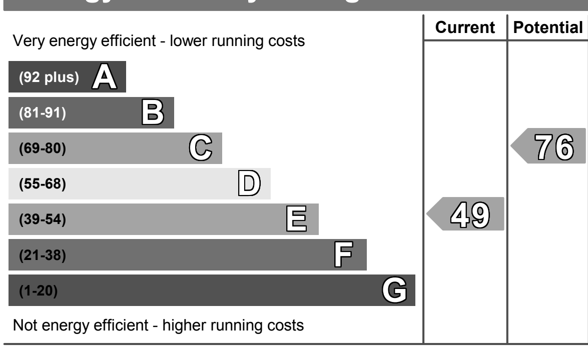
Estimated energy costs of dwelling for 3 years	**£5,367**
Over 3 years you could save	**£2,865**

Estimated energy costs of this home

	Current costs	Potential costs	Potential future savings
Lighting	£375 over 3 years	£207 over 3 years	You could save £2,865 over 3 years
Heating	£4,443 over 3 years	£2,073 over 3 years	
Hot water	£549 over 3 years	£222 over 3 years	
Totals:	**£5,367**	**£2,502**	

These figures show how much the average household would spend in this property for heating, lighting and hot water. This excludes energy use for running appliances like TVs, computers and cookers, and any electricity generated by microgeneration.

Energy Efficiency Rating



The graph shows the current energy efficiency of your home.

The higher the rating the lower your fuel bills are likely to be.

The potential rating shows the effect of undertaking the recommendations on page 3.

The average energy efficiency rating for a dwelling in England and Wales is band D (rating 60).

Top actions you can take to save money and make your home more efficient

Recommended measures	Indicative cost	Typical savings over 3 years	Available with Green Deal
1 Increase loft insulation to 270 mm	£100 - £350	£141	✔
2 Cavity wall insulation	£500 - £1,500	£537	✔
3 Draught proofing	£80 - £120	£78	✔

See page 3 for a full list of recommendations for this property.

To find out more about the recommended measures and other actions you could take today to save money, visit **www.direct.gov.uk/savingenergy** or call **0300 123 1234** (standard national rate). When the Green Deal launches, it may allow you to make your home warmer and cheaper to run at no up-front cost.

Summary of this home’s energy performance related features

Element	Description	Energy Efficiency
Walls	Cavity wall, as built, partial insulation (assumed)	★★★☆☆
Roof	Pitched, 75 mm loft insulation	★★★☆☆
Floor	Solid, no insulation (assumed)	–
Windows	Partial double glazing	★★☆☆☆
Main heating	Boiler and radiators, mains gas	★★★☆☆
Main heating controls	Programmer, room thermostat and TRVs	★★★★☆
Secondary heating	None	–
Hot water	From main system	★★★☆☆
Lighting	Low energy lighting in 17% of fixed outlets	★★☆☆☆

Current primary energy use per square metre of floor area: 298 kWh/m² per year

The assessment does not take into consideration the physical condition of any element. ‘Assumed’ means that the insulation could not be inspected and an assumption has been made in the methodology based on age and type of construction.

Low and zero carbon energy sources

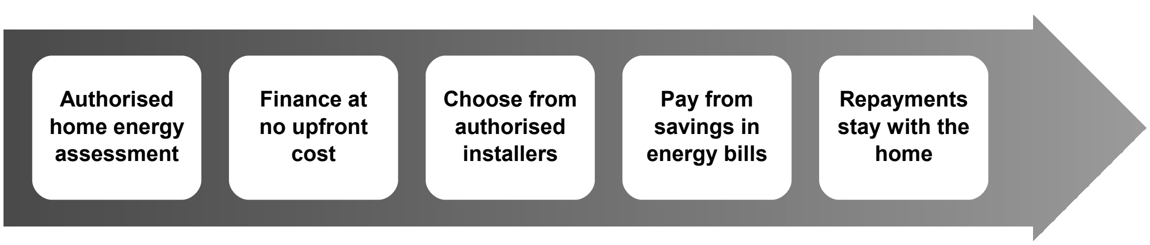
Low and zero carbon energy sources are sources of energy that release either very little or no carbon dioxide into the atmosphere when they are used. Installing these sources may help reduce energy bills as well as cutting carbon. There are none provided for this home.

Opportunity to benefit from a Green Deal on this property

When the Green Deal launches, it may enable tenants or owners to improve the property they live in to make it more energy efficient, more comfortable and cheaper to run, without having to pay for the work upfront. To see which measures are recommended for this property, please turn to page 3. You can choose which measures you want and ask for a quote from an authorised Green Deal provider. They will organise installation by an authorised installer. You pay for the improvements over time through your electricity bill, at a level no greater than the estimated savings to energy bills. If you move home, the Green Deal charge stays with the property and the repayments pass to the new bill payer.

For householders in receipt of income-related benefits, additional help may be available.

To find out more, visit **www.direct.gov.uk/savingenergy** or call **0300 123 1234**.



Recommendations

The measures below will improve the energy performance of your dwelling. The performance ratings after improvements listed below are cumulative; that is, they assume the improvements have been installed in the order that they appear in the table. Further information about the recommended measures and other simple actions you could take today to save money is available at **www.direct.gov.uk/savingenergy**. Before installing measures, you should make sure you have secured the appropriate permissions, where necessary. Such permissions might include permission from your landlord (if you are a tenant) or approval under Building Regulations for certain types of work.

Measures with a green tick ✔ are likely to be fully financed through the Green Deal, when the scheme launches, since the cost of the measures should be covered by the energy they save. Additional support may be available for homes where solid wall insulation is recommended. If you want to take up measures with an orange tick ✔, be aware you may need to contribute some payment up-front.

Recommended measures	Indicative cost	Typical savings per year	Rating after improvement	Green Deal finance
Increase loft insulation to 270 mm	£100 - £350	£47	E 51	✔
Cavity wall insulation	£500 - £1,500	£179	D 59	✔
Draught proofing	£80 - £120	£26	D 60	✔
Low energy lighting for all fixed outlets	£50	£43	D 61	
Replace boiler with new condensing boiler	£2,200 - £3,000	£339	C 74	✔
Solar water heating	£4,000 - £6,000	£34	C 75	✔
Replace single glazed windows with low-E double glazing	£3,300 - £6,500	£41	C 76	✔

Alternative measures

There are alternative measures below which you could also consider for your home.

- External insulation with cavity wall insulation
- Biomass boiler (Exempted Appliance if in Smoke Control Area)
- Air or ground source heat pump
- Micro CHP

Choosing the right package

Visit **www.epcadviser.direct.gov.uk**, our online tool which uses information from this EPC to show you how to save money on your fuel bills. You can use this tool to personalise your Green Deal package.

Directgov
Public services all in one place

Green Deal package	Typical annual savings
Loft insulation	**Total savings of £587**
Cavity wall insulation	
Draught proofing	
Condensing boiler	
Electricity/gas/other fuel savings	£0 / £587 / £0

You could finance this package of measures under the Green Deal. It could **save you £587 a year** in energy costs, based on typical energy use. Some or all of this saving would be recouped through the charge on your bill.

About this document

The Energy Performance Certificate for this dwelling was produced following an energy assessment undertaken by a qualified assessor, accredited by AAA Energy Assessors Ltd. You can get contact details of the accreditation scheme at www.aaa.co.uk, together with details of their procedures for confirming authenticity of a certificate and for making a complaint. A copy of this EPC has been lodged on a national register. It will be publicly available and some of the underlying data may be shared with others for the purposes of research, compliance and direct mailing of relevant energy efficiency information. The current property owner and/or tenant may opt out of having this information disclosed.

Assessor's accreditation number:	AAA_123456
Assessor's name:	John Smith
Phone number:	030 5555 1234
E-mail address:	john.smith@isp.net
Related party disclosure:	No related party

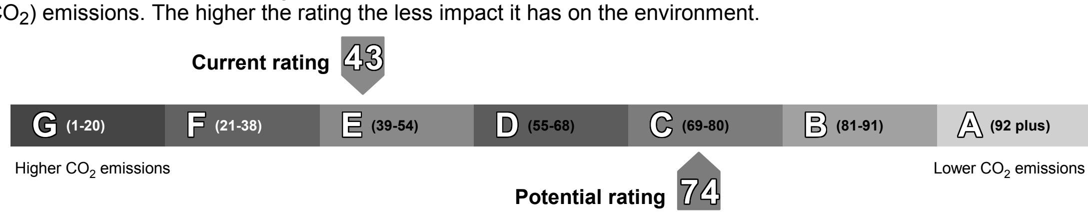
Further information about Energy Performance Certificates can be found under Frequently Asked Questions at **www.epcregister.com**.

About the impact of buildings on the environment

One of the biggest contributors to global warming is carbon dioxide. The energy we use for heating, lighting and power in homes produces over a quarter of the UK's carbon dioxide emissions.

The average household causes about 6 tonnes of carbon dioxide every year. Based on this assessment, your home currently produces approximately 9.5 tonnes of carbon dioxide every year. Adopting the recommendations in this report can reduce emissions and protect the environment. If you were to install these recommendations you could reduce this amount by 5.5 tonnes per year. You could reduce emissions even more by switching to renewable energy sources.

The environmental impact rating is a measure of a home's impact on the environment in terms of carbon dioxide (CO_2) emissions. The higher the rating the less impact it has on the environment.



Your home's heat demand

For most homes, the vast majority of energy costs derive from heating the home. Where applicable, this table shows the energy that could be saved in this property by insulating the loft and walls, based on typical energy use (shown within brackets as it is a reduction in energy use).

Heat demand	Existing dwelling	Impact of loft insulation	Impact of cavity wall insulation	Impact of solid wall insulation
Space heating (kWh per year)	22,154	(1179)	(4535)	N/A
Water heating (kWh per year)	2,792			

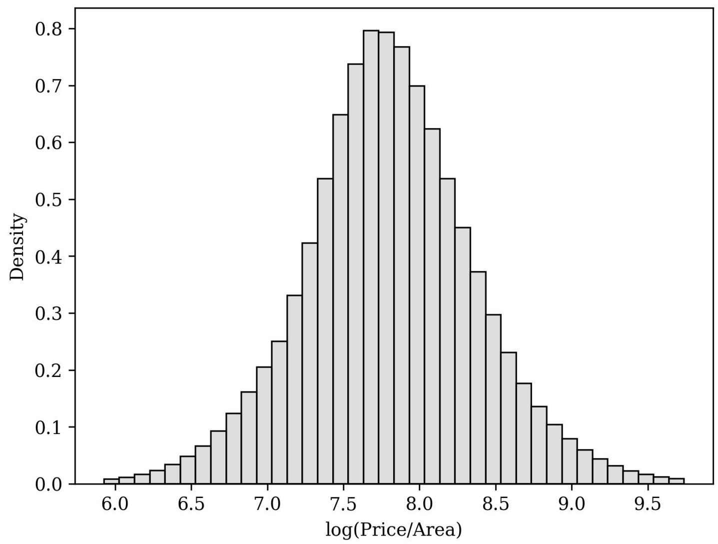
Addendum

This dwelling may have narrow cavities and so requires further investigation to determine which type of cavity wall insulation is best suited.

IA.2.2 Estimating the baseline model

Figure IA.7 shows the distribution of the logarithm of the price per unit area in the complied data. The figure shows that the distribution of the price per unit area is approximately log-normal. Therefore, using the logarithm of the price per unit area as the dependent variable in Equation (1) in Section 3.1 helps us assume that the residual follows a conditional normal distribution, in addition to being zero-mean and homoskedastic.

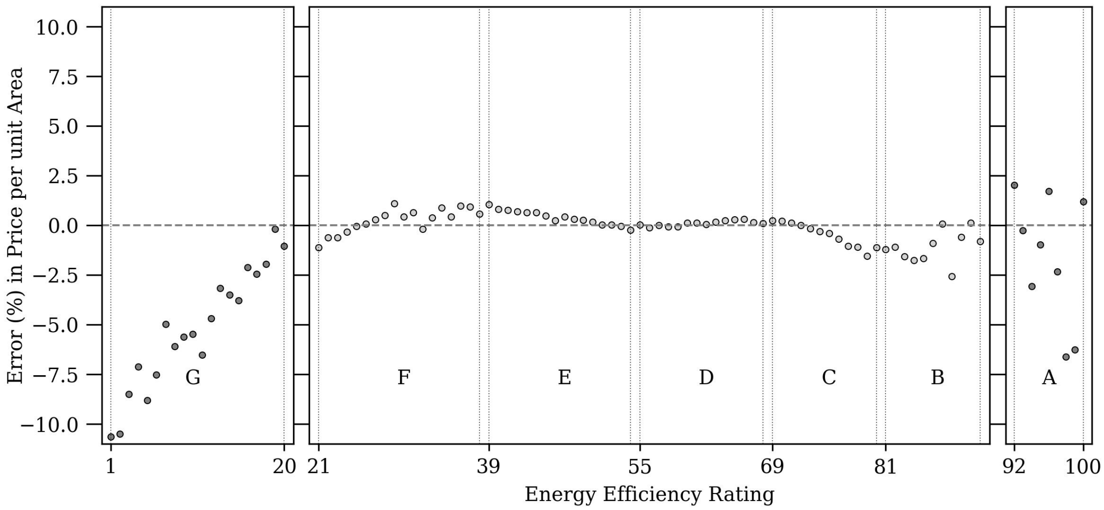
Figure IA.7: Dependent variable



This figure shows the distribution of the logarithm of the price per unit area in the complied data. The x-axis represents the value of the dependent variable and the y-axis shows the density.

Figure IA.8 plots the conditional mean of the residual $\mathbb{E}[\varepsilon_{ihrt}|\mathrm{S}_{ih}]$ (y-axis) obtained from Equation (1) for each numerical energy efficiency rating S_{ih} (x-axis). We obtain the conditional expectations as follows. First, we obtain the residual for each transaction in the regression sample by subtracting the actual values of the target variable, that is, $\log(Price/Area)$, from the fitted (or predicted) values. Then we group transactions by their current energy efficiency scores $\mathrm{S}_{ih} \in \{1, 2, ...100\}$. For each of the hundred groups thus obtained, we take the mean of the residuals and then plot them. The figure shows that $\mathbb{E}[\varepsilon_{ihrt}|\mathrm{S}_{ih}] \neq 0$ for

Figure IA.8: Conditional expectation of residuals



This figures plots the conditional mean of the residual $\mathbb{E}[\varepsilon_{ihrt}|\mathrm{S}_{ih}]$ (y-axis) obtained from Equation (1) for each numerical energy efficiency score S_{ih} (x-axis). We obtain the conditional expectations as follows. First, we obtain the residual for each transaction in the regression sample by subtracting the actual values of the target variable ($\log(Price/Area)$) from the fitted (or predicted) values. Then we group transactions by their current energy efficiency scores $\mathrm{S}_{ih} \in \{1, 2, ...100\}$. For each of the 100 groups thus obtained, we take the mean of the residuals and then plot them in this figure.

properties with energy efficiency ratings less than 21 (label G) or greater than 91 (label A). Indeed, when properties with all ratings are included, we find that the estimate for energy premium reported in Column (2) of Table 1 in Section 3.2.1 is biased upwards from 16.54 bps to 19.42 bps.

IA.2.3 Premium across different levels of aggregation

This section reports the estimates for the energy premium corresponding to different levels of aggregation of energy efficiency ratings. The main objective of this analysis is to validate that our conclusions remain robust to the potential discontinuities around different labels or groups into which the energy efficiency ratings are typically categorised into. Table IA.4 shows four common levels of aggregation deployed in the literature. In the main body of the

Table IA.4: Energy rating aggregations

Energy Rating	Energy Label	Energy Label Group	Energy Classification
92+	A		Green
81-91	B	BC	
69-80	C		
55-68	D	DE	Brown
39-54	E		
21-38	F	FG	
01-20	G		

This table shows the four common levels of aggregation deployed in the literature. The first two columns represent the official ratings and labels used by the UK Department for Levelling Up, Housing & Communities. The second two columns represent classifications typically used in the literature. Green (Brown) labels are often referred to as Sustainable (Unsustainable).

manuscript, we focus our discussion on numerical energy efficiency ratings, because all other levels of aggregation are derived from them.

Equation (1) in Section 3.1 outlines the regression specification corresponding to the numerical energy efficiency rating of dwelling h associated with transaction i as S_{ih}. We represent the corresponding *label* as $\texttt{Label}(i, h)$, the corresponding *group* as $\texttt{Group}(i, h)$, and the corresponding *classification* as $\texttt{Class}(i, h)$. Therefore, for a property with $\mathrm{S}_{ih} = 73$, we have $\texttt{Label}(i, h) =$ "C", $\texttt{Group}(i, h) =$ "BC", and $\texttt{Class}(i, h) =$ "Green", as per Table IA.4. With the dependent variable in our model as the logarithm of transaction price per unit area of the underlying property, denoted by $\log{(P/A)_{ihrt}}$, we run three hedonic regression specifications, one for each of the three categorical aggregation levels of energy efficiency ratings:

$$\log{(P/A)_{ihrt}} = \alpha_r + \delta_t + \xi_{\texttt{Label}(i,h)} + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt} + \varepsilon_{ihrt}, \tag{IA1a}$$

$$\log{(P/A)_{ihrt}} = \alpha_r + \delta_t + \xi_{\texttt{Group}(i,h)} + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt} + \varepsilon_{ihrt}, \tag{IA1b}$$

$$\log{(P/A)_{ihrt}} = \alpha_r + \delta_t + \xi_{\texttt{Class}(i,h)} + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt} + \varepsilon_{ihrt}, \tag{IA1c}$$

where all symbols have the same meaning as that in Equation (1) in Section 3.1. The parameters of interest are $\xi_{\texttt{Label}(i,h)}$, $\xi_{\texttt{Group}(i,h)}$, and $\xi_{\texttt{Class}(i,h)}$, which can be interpreted as the energy efficiency label, group, and classification specific fixed effects in Equations (IA1a), (IA1b), and (IA1c) respectively.

Table IA.5 presents the parameter estimates obtained for different levels of aggregations of energy eficiency ratings. Columns (1) and (2) replicate the results reported in Columns (1) and (2) of Table 1 in Section 3.2.1. Columns (3), (4), and (5) provide estimates for $\xi_{\texttt{Label}(i,h)}$, $\xi_{\texttt{Group}(i,h)}$, and $\xi_{\texttt{Class}(i,h)}$ corresponding to Equations (IA1a), (IA1b), and (IA1c), respectively. We obtain an adjusted R-squared greater than 78% for each specification, and all estimates that are significant at a 99% confidence level. As discussed in the main body of the manuscript, the inclusion of properties with energy efficiency ratings less than 21 (label G) and greater than 91 (label A) biases the estimate for energy premium upwards, from 0.165% in Column (1) to 0.194% in Column (2). Column (3) shows that properties with labels A (+20.1%), B (+16.1%), C (+16.1%), D (+14.8%), E (+12.4%), F (+9.6%) command a premium over those with label G, which is the omitted category. Column (4) shows that properties grouped into BC and DE command a 7.7% and 6% premium over those grouped into FG (omitted category), respectively. Lastly, Column (5) shows that properties classified as 'Green' command a 1.9% premium over those classified as 'Brown' (omitted category).

We define the *range* of energy premium as the difference between the price of an otherwise identical property with highest energy efficiency rating minus the that of the lowest rating. The range implied by the numerical energy ratings ($19.21\% = 0.194\% \times 99$) in Column (2) and the alphabetical labels (20.1%) in Column (3) are very close. Notwithstanding, at a first pass, it is quite striking to observe the substantial increase in the range of energy premium reported in Table IA.5 as we move from aggregated to more granular energy efficiency ratings, from 1.9% in Column (5) to 20.1% in Column (3). However, if we compare the averages of the estimates based on how the energy ratings were aggregated in Table IA.4, we observe that the estimates are indeed consistent across specifications. For example, if we take a weighted average of coefficients of labels D and E (14.12%)[34] and subtract it from that of labels B and

[34] Calculation: $14.12\% = (14.81\% \times 2,668,212 + 12.43\% \times 1,095,614)/(2,668,212 + 1,095,614)$

Table IA.5: Energy premium estimates for various rating aggregations

	(1)	(2)	(3)	(4)	(5)
Current Energy Score	0.165***	0.194***			
	(0.000)	(0.000)			
Current Energy Label : A			20.062***		
			(0.008)		
Current Energy Label : B			16.054***		
			(0.003)		
Current Energy Label : C			16.084***		
			(0.002)		
Current Energy Label : D			14.810***		
			(0.002)		
Current Energy Label : E			12.437***		
			(0.002)		
Current Energy Label : F			9.576***		
			(0.002)		
Current Energy Label : G			–		
Current Energy Label Group : BC				7.727***	
				(0.001)	
Current Energy Label Group : DE				6.005***	
				(0.001)	
Current Energy Label Group : FG				–	
Current Energy Classification : C+ (Green)					1.901***
					(0.000)
Current Energy Classification : D- (Brown)					–
N	5400384	5453475	5453475	5452576	5453475
Adj. R^2	0.788	0.787	0.787	0.787	0.786

This table reports the parameter estimates obtained for different levels of aggregations of energy efficiency ratings. Columns (1) and (2) replicate the results reported in Columns (1) and (2) of Table 1 in Section 3.2.1. Columns (3), (4), and (5) provide estimates for $\xi_{\texttt{Label}(i,h)}$, $\xi_{\texttt{Group}(i,h)}$, and $\xi_{\texttt{Class}(i,h)}$ corresponding to Equations (IA1a), (IA1b), and (IA1c), respectively. The dependent variable is the logarithm of price per unit area. The estimates are multiplied by 100 and should be read as percentages. The coefficients of omitted categorical variables are left blank. The p-values are reported in parentheses and are double-clustered by region and time. Lastly, p-values less than 0.10, 0.05, and 0.01 are demarcated by one (*), two (**), and three (***) stars, respectively.

C (16.08%)[35], we obtain 1.96%, which is comparable to the difference between the coefficients of groups BC and DE (1.72%) in Column (4). Similarly, the difference between the coefficient of group BC in Column (4) and the weighted average of the coefficients of groups DE and FG is 2.14%, which is comparable to the 1.9% premium commanded by properties classified as 'Green' relative to those classified as 'Brown' in Column (5).

Finally, we report the estimates for select building properties and transaction controls in Table IA.6, and those for degree days and the seven multiple deprivation indices in Table IA.7. The results for hedonic covariates act as a robustness check across specifications. The tables show that the coefficients of hedonic controls are consistent across specifications in Columns (1) through (5). The consistency of the coefficients across specifications lends additional credibility to our results.

IA.2.4 Pricing potential upgradeability

In this section, we examine whether *potential upgradeability* of dwellings is priced. We define the potential upgradeability of the dwelling h underlying transaction i as:

$$\mathrm{U}_{ih} = \frac{S_{ih}^{\text{potential}} - S_{ih}^{\text{current}}}{C_{ih}}, \tag{IA2}$$

where $S_{ih}^{\text{potential}}$ and S_{ih}^{current} denote the potential and the current energy efficiency ratings, respectively, of dwelling h underlying transaction i, and C_{ih} denotes the cost of upgrading the dwelling from S_{ih}^{current} to $S_{ih}^{\text{potential}}$. To determine whether potential upgradeability of dwellings is priced, we augment Equation (1) in Section 3.1 as follows:

$$\log{(P/A)}_{ihrt} = \alpha_r + \delta_t + \xi \mathrm{S}_{ih} + \mathrm{U}_{ih}\pi + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt} + \varepsilon_{ihrt}, \tag{IA3}$$

where π is the parameter associated with U_{ih}. We find that the potential upgradeability of dwellings is not priced, that is, $\hat{\pi}$ is insignificant. This finding is consistent with Panel (a) of Figure 15 in Section 6.1, which shows that the marginal costs of upgrading a dwelling strictly exceed the energy premium. Therefore, there is little pecuniary incentive for homeowners to consider the potential upgradeability of a dwelling at the time of the transaction.

[35] Calculation: $16.08\% = (16.05\% \times 100,024 + 16.08\% \times 1,301,976)/(100,024 + 1,301,976)$

Table IA.6: Estimates for selected building and transaction controls

	(1)	(2)	(3)	(4)	(5)
Total Floor Area	-0.277***	-0.276***	-0.276***	-0.276***	-0.277***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Habitable Rooms	1.872***	1.857***	1.851***	1.860***	1.873***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Property Type : Bungalow	24.353***	24.270***	24.014***	23.862***	23.809***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Property Type : Flat	1.905***	1.897***	2.092***	2.085***	2.080***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Property Type : House	9.766***	9.703***	9.500***	9.405***	9.381***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Property Type : Maisonette	–	–	–	–	–
New : No	–	–	–	–	–
New : Yes	3.460***	3.412***	3.596***	3.654***	3.640***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Construction Age Band : 1900 prior	7.943***	8.019***	8.019***	7.965***	7.831***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Construction Age Band : 1900-1929	–	–	–	–	–
Construction Age Band : 1930-1949	3.228***	3.198***	3.345***	3.485***	3.604***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Construction Age Band : 1950-1966	1.601***	1.510***	1.793***	2.087***	2.316***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Construction Age Band : 1967-1975	1.639***	1.500***	1.818***	2.175***	2.497***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Construction Age Band : 1976-1982	4.263***	4.036***	4.524***	5.017***	5.454***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Construction Age Band : 1983-1990	7.927***	7.650***	8.217***	8.803***	9.294***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Construction Age Band : 1991-1995	10.650***	10.358***	10.925***	11.536***	12.017***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Construction Age Band : 1996-2002	11.624***	11.217***	12.111***	12.703***	13.152***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Construction Age Band : 2003-2006	10.575***	10.044***	11.532***	11.952***	12.312***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Construction Age Band : 2007 onwards	10.203***	9.613***	11.520***	11.918***	12.265***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Tenure : Owner Occupied	13.854***	13.782***	13.728***	13.699***	13.691***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Tenure : Rental (Private)	8.324***	8.326***	8.217***	8.143***	8.118***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Tenure : Rental (Social)	–	–	–	–	–
Ownership : F	6.291***	6.411***	6.389***	6.377***	6.371***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Ownership : L	–	–	–	–	–
N	5400384	5453475	5453475	5452576	5453475
Adj. R^2	0.788	0.787	0.787	0.787	0.786

This table reports the parameter estimates obtained for different levels of aggregations of energy efficiency ratings. Columns (1) through (5) correspond to Columns (1) through (5) in Table IA.5, respectively. The dependent variable is the logarithm of price per unit area. The estimates are multiplied by 100 and should be read as percentages. The coefficients of omitted categorical variables are left blank. The p-values are reported in parentheses and are double-clustered by region and time. Lastly, p-values less than 0.10, 0.05, and 0.01 are demarcated by one (*), two (**), and three (***) stars, respectively.

Table IA.7: Estimates for location-specific controls

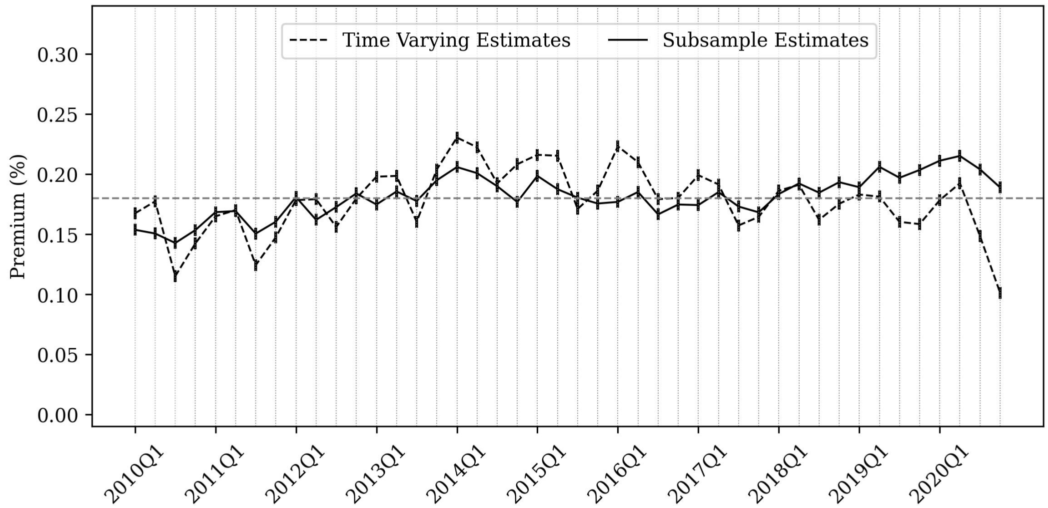
	(1)	(2)	(3)	(4)	(5)
Degree Days	-0.084**	-0.078**	-0.078**	-0.080**	-0.087**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Income Index	17.198***	17.170***	17.137***	17.138***	17.141***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Employment Index	0.891	1.010	1.005	1.013	1.040
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Health Deprivation Index	-4.840***	-4.787***	-4.818***	-4.879***	-5.010***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Education Index	43.058***	43.181***	43.118***	43.092***	43.122***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Crime Index	5.819***	5.876***	5.877***	5.871***	5.820***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Housing Barrier Index	-2.555***	-2.709***	-2.695***	-2.630***	-2.439***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Living Environment Index	-1.633***	-1.691***	-1.592***	-1.402***	-1.137***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
N	5400384	5453475	5453475	5452576	5453475
Adj. R^2	0.788	0.787	0.787	0.787	0.786

This table reports the estimates for the degree days and the multiple deprivation indices obtained for different levels of aggregations of energy efficiency ratings. Columns (1) through (5) correspond to Columns (1) through (5) in Table IA.5, respectively. The dependent variable is the logarithm of price per unit area. The estimates are multiplied by 100 and should be read as percentages. The coefficients of omitted categorical variables are left blank. The p-values are reported in parentheses and are double-clustered by region and time. Lastly, p-values less than 0.10, 0.05, and 0.01 are demarcated by one (*), two (**), and three (***) stars, respectively.

IA.2.5 Alternative dependent variable

Section 3.3 shows that environmental impact ratings of dwellings are highly correlated with their energy efficiency ratings (95% with a t-statistic of 8.16×10^3). Environmental impact ratings are assigned between 1 and 100 based on dwelling emissions. Dwellings with higher environmental impact ratings generate lower emissions. The high correlation between the two measures indicates that insights obtained from examining homeowner valuation of dwelling sustainability can be readily applied to appraise investments in climate change mitigation.

Figure IA.9: Alternative dependent variable



This figure tracks the evolution of premium associated with environmental impact ratings over time. The solid line plots estimates obtained from period-wise subsample regressions, and the dashed line plots the estimates obtained from the time-interacted effects. The horizontal dashed grey line represents the estimate obtained over the full sample.

In this section, we re-estimate Equation (1) in Section 3.1 by replacing energy efficiency ratings of the dwellings underlying the transactions by their environmental impact ratings.[36] We observe that a unit increase in the environmental impact rating of a dwelling is associated with a premium of 17.97 bps, with a t-statistic of 75.3 and an adjusted R-squared of 78.8%. The proximity of the premium associated with environmental impact ratings and the energy premium (16.54 bps) is unsurprising given the high correlation between the two measures.

Next, we re-estimate Equations (3) and (4) in Section 4.2 to examine how the premium associated with environmental impact ratings evolves over time. The results are reported in Figure IA.9. The solid line plots estimates obtained from period-wise subsample regressions, and the dashed line plots the estimates implied by the time-interacted effects. The horizontal dashed grey line represents the estimate obtained over the full sample. Overall, we observe that the premium associated with environmental impact ratings is temporally persistent.

[36] We restrict the sample dwellings with energy efficiency ratings between 21 and 91.

Table IA.8: Energy premium by tenure and urbanisation

Tenure	RU Code	Premium	Error	p-value	Observations	Adj R^2
Owner Occupied	1	0.16	0.01	0.00	415,231	0.57
	2	0.18	0.01	0.00	586,189	0.71
	3	0.17	0.01	0.00	637,296	0.74
	4	0.19	0.00	0.00	1,289,461	0.77
	5	0.30	0.01	0.00	156,688	0.66
	6	0.19	0.01	0.00	1,461,268	0.84
Rental (Private)	1	0.07	0.02	0.00	34,106	0.54
	2	0.04	0.02	0.03	48,795	0.70
	3	0.11	0.02	0.00	57,832	0.72
	4	0.08	0.01	0.00	151,673	0.78
	5	0.14	0.03	0.00	18,448	0.58
	6	0.10	0.01	0.00	228,970	0.84

This table reports the estimates for energy premium on subsamples sorted by tenure and rural-urban classifications (RUC). The rural-urban classifications are published by the Department for Environment, Food & Rural Affairs, and categorise local authority districts in the United Kingdom from most rural (1) to most urban (6). The columns titled "Tenure" and "RU Code" identify the tenure and urbanisation-specific subsample. The column titled "Premium" reports the subsample-specific energy premium obtained using Equation (1) in Section 3.1. The columns titled "Error" and "p-value" report the corresponding standard errors and p-values, respectively. The column titled "Observation" reports the sample size and the column titled "Adj R^2" reports the adjusted R-squared corresponding to the regression.

IA.3 Supplement to heterogeneity in energy premium

This appendix supplements Section 4 in the main body of the manuscript.

Table IA.8 reports the estimates for energy premium on subsamples sorted by tenure and rural-urban classifications (RUC) published by the Department for Environment, Food & Rural Affairs. Table IA.8 reports energy premium estimates reported for subsamples sorted by tenure and property type. The tables show that the tenurial spread in energy premium is persistent across regions with different levels of urbanisation and property types, respectively. Table IA.8 further shows that marginal savings are homogenous across market segments.

Table IA.9: Energy premium by tenure and property type

Tenure	Property Type	Premium	Error	p-value	Observations	Adj R^2	MS	MC
Owner Occupied	House	0.23	0.00	0.00	2,836,170	0.81	0.01	0.49
	Flat	0.14	0.01	0.00	312,204	0.79	0.01	0.23
	Bungalow	0.28	0.00	0.00	433,937	0.72	0.01	0.40
	Maisonette	0.27	0.01	0.00	47,859	0.80	0.01	0.21
Rental (Private)	House	0.16	0.01	0.00	197,350	0.84	0.01	0.65
	Flat	0.11	0.01	0.00	82,625	0.77	0.01	0.23
	Bungalow	0.19	0.02	0.00	14,034	0.71	0.01	0.45
	Maisonette	0.05	0.04	0.18	9,300	0.74	0.01	0.22

This table reports the estimates for energy premium on subsamples sorted by tenure and property type. The columns titled "Tenure" and "Property Type" identify the subsample corresponding to a given tenure and property type. The column titled "Premium" reports the subsample-specific energy premium obtained using Equation (1) in Section 3.1. The columns titled "Error" and "p-value" report the corresponding standard errors and p-values, respectively. The column titled "Observation" reports the sample size and the column titled "Adj R^2" reports the adjusted R-squared corresponding to the regression. The columns titled "MS" and "MC" report the unconditional expectations of the marginal savings and costs, respectively, computed over that subsample (see Section 5.2 for details on computation).

IA.4 Supplement to demand and regulatory impact

This appendix supplements Section 6 in the main body of the manuscript.

IA.4.1 Details on the logistic model

In Section 6.2.1, we examine the impact of the Minimum Energy Efficiency Standard (MEES) on homeowner decisions to improve dwelling energy efficiency. To formalise our findings, we estimate a logistic regression to measure the change in the probability of rating improvements for a dwelling belonging to a given market segment and label post-regulation. In this section, we describe the logistic model.

For a given market segment (owner-occupied, private-rental, or both) and label (all labels, or labels G through B), we estimate the following model:

$$\log\left(\frac{\Pr\{\text{Upgrade}=1\}}{\Pr\{\text{Upgrade}=0\}}\right) = \alpha + \beta \mathbb{1}_{Regulation}, \tag{IA4}$$

where $\Pr\{\text{Upgrade} = 1\}$ denotes the probability of an upgrade and $\mathbb{1}_{Regulation}$ is an indicator variable for the period following the regulatory approval. The term α captures the probability of a rating improvement in the absence of regulation. The term β captures the incremental impact of the regulation on the probability of a rating improvement.

We measure the change in the probability of rating improvement following the regulation as $\hat{\beta} - \hat{\alpha}$, and ascertain the statistical significance of this change using the p-value associated with $\hat{\beta}$. Table 3 in the main body of the manuscript reports the results.

IA.4.2 Details on the difference in differences method

In Section 6.2.3, we use a difference in differences method to investigate whether the targeted properties that did not upgrade following the Minimum Energy Efficiency Standard (MEES) transacted at a discount. This section arrives at Equation (11) from first principles.

Consider the following conditional expectation function for the transactions that occurred before MEES was approved:

$$\begin{aligned}\mathbb{E}\left[\log{(P/A)}_{ihrt}^{\text{untreated, pre-MEES}}\right] &= \alpha_r + \delta_t + \xi \mathrm{S}_{ih} + \mu_t(\mathbb{1}_t \times \mathrm{S}_{ih}) \\ &\quad + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt},\end{aligned} \tag{IA5}$$

where the unit of observation in our model is the same as that in Equation (4) in Section 4.2 with $\log{(P/A)}_{ihrt}$ as the target variable; and each symbol has the same meaning as that in Equation (4). Let $\lambda_{\text{Regulation}}$ denote the fixed effect of MEES on the target variable (for both treatment and control groups) such that:

$$\begin{aligned}\mathbb{E}\left[\log{(P/A)}_{ihrt}^{\text{untreated, post-MEES}}\right] &= \mathbb{E}\left[\log{(P/A)}_{ihrt}^{\text{untreated, pre-MEES}}\right] + \lambda_{\text{Regulation}} \\ &= \alpha_r + \delta_t + \xi \mathrm{S}_{ih} + \mu_t(\mathbb{1}_t \times \mathrm{S}_{ih}) \\ &\quad + \lambda_{\text{Regulation}} \\ &\quad + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt}.\end{aligned} \tag{IA6}$$

Finally, let $\rho_{\text{Regulation}}$ denote the casual effect of treatment such that:

$$\begin{aligned}\mathbb{E}\left[\log\left(P/A\right)_{ihrt}^{\text{treated, post-MEES}}\right] &= \mathbb{E}\left[\log\left(P/A\right)_{ihrt}^{\text{untreated, post-MEES}}\right] + \rho_{\text{Regulation}} \\ &= \alpha_r + \delta_t + \xi \mathrm{S}_{ih} + \mu_t(\mathbb{1}_t \times \mathrm{S}_{ih}) \\ &\quad + \lambda_{\text{Regulation}} + \rho_{\text{Regulation}} X_i \\ &\quad + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt} + \varepsilon_{ihrt},\end{aligned} \tag{IA7}$$

where X_i is an indicator variable for treatment; $X_i = 1$ when transaction i takes place after March 26, 2015 *and* the energy efficiency rating of the underlying property is less than 39; $X_i = 0$ otherwise. This yields Equation (11) in Section 6.2.3.

IA.4.3 Details on the regression discontinuity method

In Section 6.2.3, we use a regression discontinuity method to investigate whether the targeted properties that did not upgrade following the Minimum Energy Efficiency Standard (MEES) transacted at a discount. This section arrives at Equation (12) from first principles.

Regression discontinuity designs can be either *sharp* or *fuzzy*. Sharp designs are relevant to settings where the assignment of treatment is perfectly known, whereas fuzzy designs are a two-step IV-like approach used in settings where the assignment of treatment around the cut-off is not perfectly known (for example, when we are trying to predict assignment instead of knowing it). Since we have perfect information about energy ratings, the corresponding labels, and their treatment, we deploy a sharp regression discontinuity design.

We denote the numerical cutoff at which a property is labelled E as $c = 39$. The unit of observation in our model is the same as that in Equation (4) in Section 4.2 with $\log\left(P/A\right)_{ihrt}$ as the target variable. We distinguish between properties that receive the treatment (properties that were impacted by the policy) as $\log\left(P/A\right)_{ihrt}^{1}$ and those that do not as $\log\left(P/A\right)_{ihrt}^{0}$. Consider the following conditional expectation formulation:

$$\begin{aligned}\mathbb{E}\left[\log\left(P/A\right)_{ihrt}^{0}\right] &= \alpha_r + \delta_t + \xi(\mathrm{S}_{ih} - c) + \mu_t(\mathbb{1}_t \times (\mathrm{S}_{ih} - c)) \\ &\quad + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt},\end{aligned} \tag{IA8}$$

where $\mathrm{S}_{ih} - c$ denotes the energy efficiency rating of a property centred around the regulatory threshold c, and all other symbols have exactly the same meaning as that in Equation (4). Let ρ denote the casual effect of treatment such that:

$$\log{(P/A)}^1_{ihrt} = \log{(P/A)}^0_{ihrt} + \rho. \tag{IA9}$$

This yields the following regression model:

$$\begin{aligned}\log{(P/A)}_{ihrt} = \alpha_r + \delta_t + \xi(\mathrm{S}_{ih} - c) + \mu_t(\mathbb{1}_t \times (\mathrm{S}_{ih} - c)) + \rho X_i \\ + \theta \mathrm{B}_h + \gamma \mathrm{T}_i + \nu \mathrm{IMD}_{rt} + \omega \mathrm{DD}_{rt} + \varepsilon_{ihrt},\end{aligned} \tag{IA10}$$

where X_i is an indicator variable defined as:

$$\mathrm{X}_i = \begin{cases} 0 & \text{if } S_{ih} \geq c \\ 1 & \text{if } S_{ih} < c \end{cases} \tag{IA11}$$

and ρ is the causal effect of interest. This yields Equation (12) in Section 6.2.3. Note that because Equation (12) models differences in outcomes between treatment and control groups during the same time period, it does not require the parallel trends assumption like Equation (11).

IA.4.4 Regulatory exemptions

The difference in differences and regression discontinuity methods in Section 6.2.3 show that the affected dwellings which did not upgrade post-regulation were not transacted a discount. Table IA.10 provides a partial list and description of exemptions from the Minimum Energy Efficiency Standards (MEES) that landlords can claim, adapted from the Guidance on PRS Exemptions published by the UK Government. We attribute an insignificant treatment effect in Section 6.2.3 to the ability of landlords to claim exemptions outlined in Table IA.10. For example, the typical property affected by the MEES (but which did not undergo the requisite rating improvement) requires a significantly higher capital expenditure than the regulatory threshold specified under the 'High Cost' exemption. Similarly, affected properties that cannot be upgraded are also exempt under the 'All Improvements Made' clause.

Table IA.10: Exemptions to Minimum Energy Efficiency Standards

Exemption	Description
High Cost	The prohibition on letting property below an EPC rating of E does not apply if the cost of making even the cheapest recommended improvement would exceed £3,500.
All Improvements Made	Where all the relevant energy efficiency improvements for the property have been made (or there are none that can be made) and the property remains sub-standard.
Wall Insulation	The landlord has obtained written expert advice indicating that the measure is not appropriate for the property due to its potential negative impact on the fabric or structure of the property.
Consent	Certain energy efficiency improvements may legally require third party consent (e.g., local authority planning consent, consent from mortgage lenders, etc.) before they can be installed.
Devaluation	An exemption from meeting the minimum standard will apply where the landlord has obtained a report from an independent surveyor who is on the Royal Institution of Chartered Surveyors (RICS) register of valuers advising that the installation of specific energy efficiency measures would reduce the market value of the property, or the building it forms part of, by more than 5%.
New Landlord	If a person becomes a landlord in circumstances where it would be unreasonable for them to be required to comply with the regulations immediately, a temporary 6 month exemption will apply from the date they become the landlord.

This table provides a partial list and description of exemptions from the Minimum Energy Efficiency Standards (MEES) that landlords can claim. The list has been adapted from the Guidance on PRS Exemptions published by the UK Government, available at https://www.gov.uk/government/publications/private-rented-sector-minimum-energy-efficiency-standard-exemptions/guidance-on-prs-exemptions-and-exemptions-register-evidence-requirements.

End of the Internet Appendix